Short Title: PERSONALITY PROFILES IN MULTIDIMENSIONAL SPACES

Research Article

Differentiating Abnormal, Normal, and Ideal Personality Profiles in Multidimensional Spaces

Fernando Gutiérrez[a,b], Josep Maria Peri[a], Anton Aluja[c,d], Eva Baillés[e], Bárbara Sureda[a], Alfonso Gutiérrez-Zotes[f,g], Gemma Vall[d,h], Natalia Calvo[g,i], Marc Ferrer[g,i], Myriam Cavero[a], Aida Mallorquí[a], Silvia Edo Villamón[j,k], Amanda Meliá de Alba[l], M. Ángeles Ruipérez Rodríguez[j]

[a] Hospital Clínic, Barcelona, Spain,
[b] IDIBAPS, Barcelona, Spain
[c] University of Lleida, Spain
[d] Biomedical Research Institute of Lleida, Spain
[e] Pompeu Fabra University, Spain
[f] Pere Virgili Health Research Institute (IISPV), Reus, Spain
[g] CIBERSAM, Spain
[h] GSS–Hospital Santa María, Lleida, Spain
[i] Vall d'Hebron University Hospital, Barcelona, Spain
[j] Jaume I University, Spain
[k] Provincial Hospital Consortium, Castellón, Spain
[l] Higher Institute of Psychological Studies (ISEP), Spain

Corresponding author

Fernando Gutiérrez, Personality Disorder Unit, Institute of Neuroscience, Hospital Clínic, Villarroel 170, 08036 Barcelona, Spain. E-mail: fguti@clinic.cat

Funding

This work was supported by project PI15/00536, part of the Plan Estatal de Investigación Científica y Técnica y de Innovación, 2013–2016, and cofinanced by the ISCIII Subdirección General de Evaluación and the European Regional Development Fund ("A way to build Europe"; PI: Fernando Gutiérrez).

Availability of data and material

The data and code that support this research are available from the corresponding author (FG) upon reasonable request.

Abstract

Current dimensional taxonomies of personality disorder (PD) establish that intense traits do not suffice to diagnose disorder, and additional constructs reflecting dysfunction are required. However, traits appear able to predict maladaptation by themselves, which might avoid duplications and simplify diagnosis. On the other hand, if trait-based diagnoses are feasible, it is the whole personality profile that should be considered, rather than individual traits. This takes us into multidimensional spaces, which have their own particular —but poorly understood— logic. The present study examines how profile-level differences between normal and disordered subjects can be used for diagnosis. The Dimensional Assessment of Personality Pathology – Basic Questionnaire (DAPP-BQ) and the Personality Inventory for DSM-5 (PID-5) were administered to a community and a clinical sample each (total n = 1,925 and 3,543 respectively). Intense traits proved to be common in the general population, so empirically-based thresholds are indispensable not to take as abnormal what is at most unideal. Profile-level parameters such as Euclidean and Mahalanobis distances, outperformed individual traits in predicting mental problems, and equaled the performance of published measures of dysfunction or severity. Personality profiles can play a more central role in identifying disorder than is currently acknowledged, provided that the adequate metrics are used.

Keywords: Personality disorders; personality dysfunction; dimensional classification; multidimensional space.

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Introduction

Although dimensional models of personality disorder (PD) show considerable advantages over categories (Ofrat et al., 2018), offering clear-cut criteria for diagnosis is not one of them. The collapse of categorical taxonomies has left clinicians without a simple and generally accepted (even though arbitrary) diagnostic criterion, and progress towards a new empirically-based criterion is urgently required.

Advances in this direction are thwarted by disagreements on what PD diagnosis should mainly depend upon: whether the intensity of traits, their durability and pervasiveness, or the unhappiness, malfunctioning, and psychopathology they usually cause (Leising & Zimmermann, 2011; Zimmerman et al., 2018). In this debate, the current trend is towards downplaying personality traits for diagnostic purposes. This is the case of both the Diagnostic and Statistical Manual of Mental Disorders (DSM–5; American Psychiatric Association, 2013) and the International Classification of Diseases (ICD-11; World Health Organization, 2018), in which intense traits are not enough for diagnosis, and supplementary constructs representing dysfunction or severity are required. As an advantage, this prevents overdiagnosis, as not all intense traits are indeed maladaptive, and an additional evaluative construct might be needed to ensure that these traits actually cause trouble (Leising & Zimmermann, 2011). But there are drawbacks too. Adjunctive constructs need to be clearly different from personality traits and contribute incremental information in order to compensate for increased complexity. The evidence on this respect has been mixed so far, as functioning and personality actually overlap to a considerable extent (Cruitt et al., 2019). On the other hand, reliance on adjunctive constructs disregards the well-established fact that personality traits are not aseptic descriptors of individual differences, but are powerful predictors of maladaptation in their own right (Clark & Ro, 2014; Ozer & Benet-Martínez, 2006; Vall et al., 2015). The best known example is neuroticism, which is the single strongest risk factor for common mental disorders such as anxiety and depression (Ormel et al., 2013), as well as a reliable predictor of drug use, low well-being, interpersonal difficulties, health problems, and reduced life expectancy (Jeronimus et al., 2016; Ozer & Benet-Martínez, 2006). In fact, neuroticism is among the most detrimental risk factors ever found (Lahey, 2009). More generally, plenty other normal-range and pathological personality traits have proven to be related to negative life outcomes, mental distress, and psychopathology (Lynam & Miller, 2019; Michelini et al., 2021; Mullins-Sweat et al., 2019; Vall et al., 2015). All this calls for further examination on whether traits themselves can play a role in deciding diagnosis.

If such is the case, it may not be each individual trait that matters for diagnosis, but the whole profile, that is, the *overall* magnitude of the difference. Multi-trait configurations are the natural biological units of measurement for personality (Cloninger & Zwir, 2018) and the highest interpretive level of an instrument, providing more information than any of its parts (Clark et al., 2020; Morey et al., 2011). However, analyses at the profile level are virtually nonexistent, to the point that we do not know what normal and disordered profiles should look like. For example, clinicians may consider that having two extreme traits is trivial, that having eleven is not, or that this depends on which traits we are referring to, but none of these judgments has any empirical support. In fact, we cannot infer profile-level thresholds from trait-level population norms, since the multidimensional space has its own —often counterintuitive— logic (Altman & Krzywinski, 2018). One instance is that, as the number of traits rises, it is increasingly unlikely to find a 'normal' profile (van Tilburg, 2019). Two widely used PD

questionnaires —the Dimensional Assessment of Personality Pathology - Basic Questionnaire (DAPP-BQ; Livesley & Jackson, 2009) and the Personality Inventory for DSM-5 (PID-5; Krueger et al., 2012)— can illustrate this point. Assuming a normal distribution with a pathological upper tail, the prevalence of any elevated trait (i.e., one SD above the mean, or T > 60) will be 15.9%, that of an extreme trait (two SD above, or T > 70) will be 2.3%, and the complementary probability of being statistically normal (i.e., medium or low in that trait) will then be 84.1%. However, if we transfer this logic to the whole profile, the joint probability of being normal in all traits would be as low as 4.4% in the 18-trait DAPP-BQ [$(.841^{18})*100$] and 1.3% in the 25-trait PID-5 [$(.841^{25})*100$]… provided that these estimations were right. But they are not, as we are mistakenly assuming the mutual independence of traits that actually covary in unknown ways, which strongly determines the final probabilities. This is particularly relevant to the current taxonomies of PD, whose constituent traits show higher intercorrelations than normal-range traits (Morey et al., 2022; Ringwald et al., 2021). The estimation of differences in multivariate domains has not an obvious mathematical solution (Del Giudice, 2021), and the point from which a personality profile suggests psychopathology can only be established empirically.

This study aims to examine how the general elevation and shape of the PID-5 and DAPP-BQ profiles differ between community and clinical populations, and whether these differences can serve diagnostic purposes. It is our contention that personality profiles can carry more weight than they currently do in the diagnosis of PDs.

Materials and Methods

Sample

The DAPP-BQ and the PID-5 were each administered to different clinical and community samples. The two clinical samples were recruited from the mental health services of six public and private hospitals in Spain. The DAPP-BQ clinical sample was composed of 1,467 outpatients, 54.3% female, aged 16 to 74 years (M = 34.7, SD = 11.1). The PID-5 clinical sample was composed of 891 outpatients, 64.2% female, aged 15 to 79 (M = 36.3, SD = 12.3). DSM-IV Axis I disorders were assessed by experienced clinicians through two non-structured interviews, the Dual Diagnosis Screening Interview (Mestre-Pintó et al., 2014) or the Structured Clinical Interview for DSM-IV Axis I Disorders (First et al., 1996), depending on the center. A quarter of all subjects presented a mild to moderate affective disorder, mainly unipolar depression, 13% an anxiety disorder including phobias, 9% mixed anxious-depressive symptoms, and one tenth presented other psychopathology such as eating disorders, substance-related disorders, impulse control disorders, and somatoform disorders, each with a frequency below 5%. No categorical diagnoses of PD were made. The two community samples were recruited from students and their acquaintances at three Spanish universities or training centers. The DAPP-BQ community sample was composed of 2,076 volunteers, 56.9% female, aged 14 to 85 (M = 38.4, SD = 15.8). The PID-5 community sample consisted of 1,034 volunteers, 57.6% female, aged 15 to 89 (M = 41.2, SD = 17.7). The study was approved by the ethical committees of the respective centers, and all patients gave their informed consent to participate.

Instruments

We used two personality instruments so as to increase generalizability. The Dimensional Assessment of Personality Pathology–Basic Questionnaire (DAPP-BQ; Livesley & Jackson, 2009) is a 290-item questionnaire rated on a 5-point scale ranging from 1 (*Very unlike me*) to 5 (*Very like me*). It assesses 18 trait grouped into four higher-order domains labeled Emotional Dysregulation, Dissocial Behavior, Inhibition, and

Compulsiveness. The Personality Inventory for DSM-5 (PID-5; Krueger et al., 2012) is a 220-item questionnaire rated on a 4-point Likert-type scale ranging from 0 (*Very false or often false*) to 3 (*Very true or often true*). It was developed to assess the 25 pathological personality traits of the alternative DSM-5 model, which can be grouped into five second-order domains: Negative Affect, Detachment, Antagonism, Disinhibition, and Psychoticism. Both instruments have proven adequate psychometric properties in their Spanish versions (Gutiérrez et al., 2017; Gutiérrez-Zotes et al., 2008).

Data Analysis

Caseness (belonging to the clinical sample) was taken as a proxy for the presence of clinically significant problems, including state psychopathology, and then as the outcome variable. DAPP-BQ and PID-5 domains and traits, expressed in *T*-scores, were tested as potential predictors of caseness at the trait level, and so were a number of profile-level variables: total score; the number of elevated ($T > 60$) and extreme traits ($T > 70$); a general factor of PD (g-PD); and the Euclidean, Mahalanobis, and shape distances, which have been proposed as the most appropriate measures of multivariate distance (Del Giudice, 2021). The g-PD captures the shared variance among traits in each questionnaire. It was obtained at the facet-level through factor analysis using maximum likelihood extraction, although unweighted least squares and principal axis factoring resulted in identical factors with Tucker's congruences $\Phi = 1$. The Euclidean distance is simply the length of the straight-line between the multivariate mean (centroid) of each individual profile and that of the community sample. Mahalanobis distance corrects Euclidean distance for the covariances, in order to take collinearity among traits into account. Shape distance measures the dissimilarity between the form of each individual profile and that of the average community profile through correlation, and is therefore irrespective of profile elevation[1]. The classificatory ability of each predictor was tested by means of logistic regressions and ROC curves. Cutoffs were selected that maximized Youden's Index, that is, the sum of sensitivity (*Se*, true positive rate) and specificity (*Sp*, true negative rate), as well as kappa concordance between the predicted and observed classifications. Areas under the ROC curve (AUC) were cross-validated through a k-fold resampling procedure: Each sample was split into five groups, and each group sequentially served to test the predictive model previously built in the remaining four groups. The procedure was repeated ten times, so each final AUC was the average of 50 cross-validated AUCs. SPSS v.24 and the R packages "OptimalCutpoint" (López-Ratón et al., 2014) and "caret" (Kuhn, 2022) were used for all analyses.

Results

Figure 1 shows that, as severity increases, profiles rise at an uneven pace, suggesting that some individual traits may be particularly good indicators of severity. Therefore, the ability to predict caseness was tested at the trait level first. On the DAPP-

[1] Euclidean distance is $D_E = \sqrt{\sum_{i-1}^{k}(x_i - \mu_i)^2}$ where x_i is the score on the i^{th} trait for each subject, and μ_i is the mean of the i^{th} trait in the community sample (in our case $z = 0$). Mahalanobis distance is $D_M = \sqrt{(x_i - \mu_i)^T S^{-1}(x_i - \mu_i)}$ where S^{-1} is the inverse of the covariance matrix and *T* indicates that vector should be transposed (covariance matrices in Supplementary Tables S1 and S2). Shape distance is $D_S = \sqrt{2 \times (1 - r_{xy})}$ where r_{xy} is the correlation between each individual profile and the average profile in the community, expressed in raw scores. More details in Del Giudice (2021).

BQ, Identity Problems outperformed all other traits with Nagelkerke's R_N^2 = .34 in logistic regression and an area under the curve AUC = .79 in ROC analysis. Other traits such as Anxiousness, Affective Lability, Self–Harm, and the Emotional Dysregulation domain were almost as good (Supplementary Table S3). On the PID-5, the best predictors were Depressivity (R_N^2 = .42, AUC = .82) and Anhedonia (R_N^2 = .37, AUC = .80), followed by Anxiousness, Detachment, and Disinhibition (Supplementary Table S4).

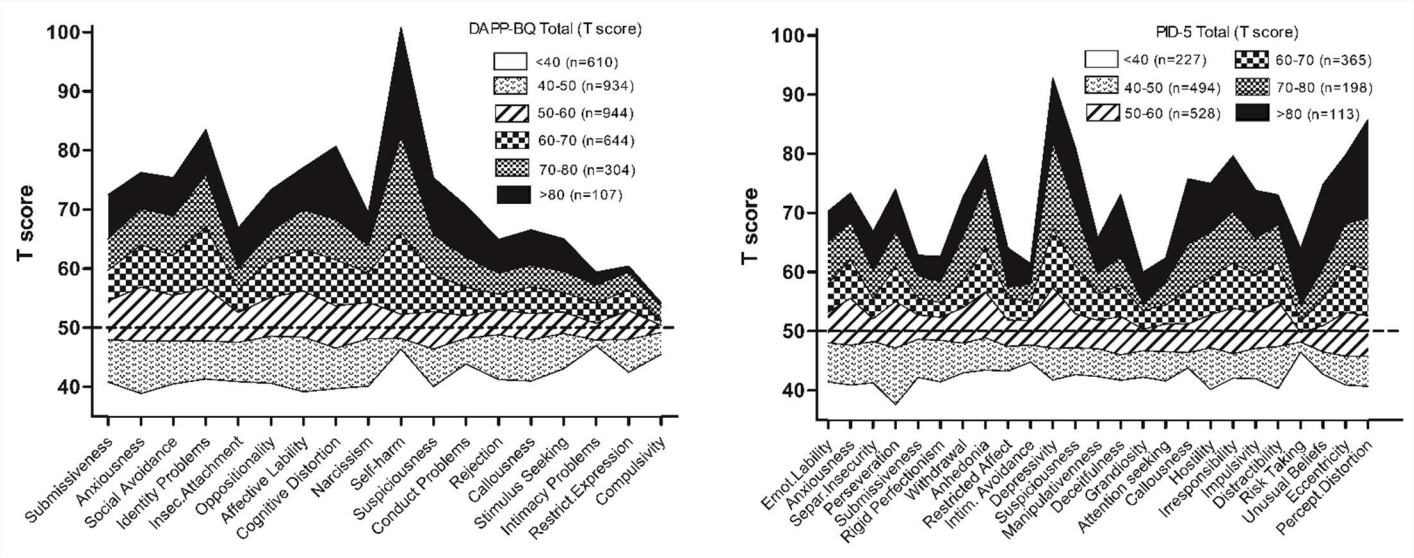

Figure 1. Profiles of the DAPP-BQ and the PID-5 for Different Levels of the Total Score

Profile-level predictors were tested in a second step. As expected, although elevated (T > 60) and extreme (T > 70) scores indicate infrequency at the trait level, they fail to do so in the multivariate space defined by the whole profile. In fact, even in the community samples, most subjects showed at least one elevated trait on either the DAPP-BQ (71.1%) or the PID-5 (78.5%) (Supplementary Tables S5 and S6). The mean number of DAPP-BQ elevated traits was 3.0 in the community versus 6.9 in the clinical sample (t = -29.5, p<.001), and was 4.0 versus 10.2 on the PID-5 (t = -25.8, p < .001). As for extreme traits (T > 70), means were respectively 0.7 versus 3.2 on the DAPP-BQ (t = -27.2, p < .001) and 1.0 versus 5.4 on the PID-5 (t = -24.9, p < .001). Thus, empirically-based thresholds are indispensable to establish clinical significance.

Elevated and extreme trait counts, DAPP-BQ and PID-5 total scores, and the general factor (g-PD) for each questionnaire were then tested as predictors of caseness. On the DAPP-BQ, the number of elevated traits showed R_N^2 = .27 in logistic regression and AUC = .76 in ROC analysis, whereas the number of extreme traits showed R_N^2 = .29 and AUC = .76 (Table 1). According to Youden's index, clinicians can consider to be cases those subjects with six or more elevated traits (sensitivity Se = .61 and specificity Sp = .80) or one or more extreme traits (Se = .72, Sp = .71). As for the PID-5, the number of elevated (R_N^2 = .34, AUC = .79) and extreme traits (R_N^2 = .38, AUC = .81) were also good predictors. In this case the best cutoffs were seven elevated traits (Se = .70, Sp = .78) or two extreme traits (Se = .72, Sp = .81). Neither the DAPP-BQ and PID-5 total scores nor the g-PDs, which might be expected to be good indicators of clinical

significance, performed better, with R^2_N between .23 and .33, and *AUC* between .74 and .78 (Table 1). In most cases, cutoffs maximizing Youden's index also maximized kappa.

Finally, specific metrics for multidimensional spaces, such as the Euclidean, Mahalanobis, and shape distances between each individual profile and the centroid of the community sample were tested. Euclidean distance was 4.0 on average in the community versus 6.2 in the clinical sample on the DAPP-BQ, and 4.8 versus 7.9 on the PID-5 (Table 1). Predictive parameters were R^2_N = .33 and .44, and *AUC* = .79 and .84, respectively. Youden's index suggested 5.3 on the DAPP-BQ (*Se* = .58, *Sp* = .85) and 5.6 on the PID-5 (*Se* = .74, *Sp* = .79) as the best cutoffs. As for Mahalanobis distance, it was 4.1 versus 6.1 on the DAPP-BQ, and 4.8 versus 7.2 on the PID-5. Predictive parameters were R^2_N = .40 and .47, and *AUC* = .82 and .85, respectively, which makes Mahalanobis distance the best predictor of caseness (Figure 2). The best cutoffs were 4.7 on the DAPP-BQ (*Se* = .75, *Sp* = .75) and 5.8 on the PID-5 (*Se* = .77, *Sp* = .80). In contrast, shape distance was a poorer predictor. All predictive models, both at the individual- and profile-level, were successfully cross-validated through a k-fold resampling procedure.

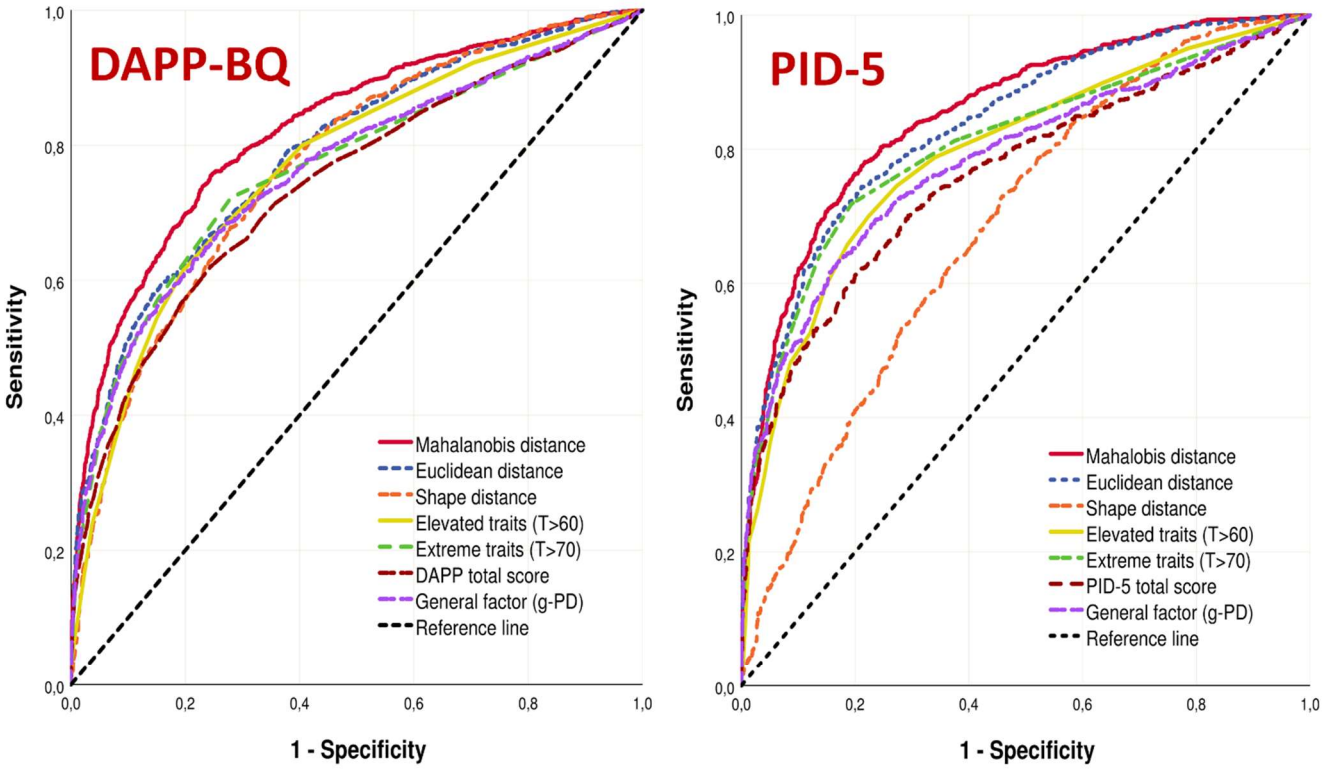

Figure 2. ROC Curves for the Profile-Level Predictors.

Table 1. Predictors of Caseness at the Profile Level: Descriptives, Logistic Regression and ROC Curve Parameters.

	Descriptives				Logistic Regression			ROC analysis			
	Community Sample		Clinical Sample								
	Mean	(SD)	Mean	(SD)	$R^2_{C\&S}$	R^2_N	Accu-racy	AUC	Cutoff	Se	Sp
DAPP-BQ											
Total score	50.0	(10.0)	60.3	(14.1)	.17	.23	.70	.74 (.72 - .75)	57	.62	.75
General factor (g-PD)	-.39	(.75)	.50	(1.0)	.20	.27	.72	.76 (.75 - .78)	.237	.63	.78
Elevated traits (T > 60)	3.0	(3.3)	6.9	(4.3)	.20	.27	.72	.76 (.75 - .78)	6	.61	.80
Extreme traits (T > 70)	0.7	(1.5)	3.2	(3.3)	.21	.29	.73	.76 (.75 - .78)	1	.72	.71
Euclidean distance (D_E)	**4.0**	**(1.4)**	**6.2**	**(2.5)**	**.25**	**.33**	**.74**	**.79 (.77 - .80)**	**5.3**	**.58**	**.85**
Mahalanobis distance (D_M)	**4.1**	**(1.2)**	**6.1**	**(2.0)**	**.30**	**.40**	**.76**	**.82 (.81 - .84)**	**4.7**	**.75**	**.75**
Shape distance (D_S)	.725	(.192)	.935	(.222)	.20	.27	.71	.77 (.75 - .78)	.769	.75	.65
PID-5											
Total score	50.0	(10.0)	62.9	(14.6)	.21	.28	.71	.76 (.74 - .78)	59	.61	.80
General factor (g-PD)	-.44	(.67)	.53	(1.0)	.25	.33	.73	.78 (.76 - .81)	.189	.64	.83
Elevated traits (T > 60)	4.0	(4.2)	10.2	(6.1)	.26	.34	.74	.79 (.77 - .81)	7	.70	.78
Extreme traits (T > 70)	1.0	(2.0)	5.4	(5.0)	.29	.38	.76	.81 (.79 - .83)	2	.72	.81
Euclidean distance (D_E)	**4.8**	**(1.5)**	**7.9**	**(3.0)**	**.33**	**.44**	**.77**	**.84 (.82 - .86)**	**5.6**	**.74**	**.79**
Mahalanobis distance (D_M)	**4.8**	**(1.3)**	**7.2**	**(1.9)**	**.35**	**.47**	**.78**	**.85 (.84 - .87)**	**5.8**	**.77**	**.80**
Shape distance (D_S)	.939	(.189)	1.06	(.181)	.10	.14	.63	.68 (.66 - .71)	.955	.73	.55

Note. $R^2_{C\&S}$ = Cox & Snell's pseudo R-squared; R^2_N = Nagelkerke's pseudo R-squared; AUC = area under the curve; Se = Sensibility; Sp = Specificity. The best predictors are in bold type.

Discussion

Classificatory systems for PD have become dimensional and multivariate, but some implications of this change are still understudied. Importantly, the logic of multidimensional spaces causes that, whereas being within the $T = 50 \pm 10$ range in each individual trait is the norm, being within this range in all traits is uncommon (van Tyburg, 2019). In terms of prevalence, this means that only 20 to 25% of the general population will exhibit no elevated traits in current dimensional taxonomies, and that many subjects will rather present with up to six or seven elevated traits. In clinical terms, it means that optimally functioning or "ideal" individuals —those described in the DSM-5 as presenting "a mostly positive [...] self-concept", an "appropriately regulated emotional life" and "reciprocal and fulfilling interpersonal relationships" (American Psychiatric Association, 2013, p. 771)— are in fact rare, and they do not actually represent "normal" personalities. Instead, four out of five normal people are either reckless, submissive, inflexibly perfectionist, disengaged, unfriendly, insecure in relationships, or a combination thereof. This is in line with the finding that enduring mental health is not the norm but the exception in the population with a prevalence of 17.3%, and that the main reason for this is a disadvantageous temperament (Schaefer et al., 2017). In the end, dimensional models present a continuum of increasingly "unideal" personalities, so that determining the point at which subjects need specialized care becomes a clinical necessity.

Our second finding is that the predictive ability of pathological personality traits appears comparable to that reported in the literature for adjunctive constructs reflecting dysfunction or severity. For example, whereas the DSM-5 functioning scale and the ICD-11 severity scale have shown *AUCs* of .83-.86 when it comes to predicting the presence of a categorical PD (Buer Christensen et al., 2019; Morey et al., 2013; Olajide et al., 2018), our personality traits achieve a similar .79-.85 regarding caseness. Also, if we assume the comparability of the coefficients of determination (Smith & McKenna, 2013), the DSM-5 functioning scale has proven able to explain between 4% and 15% of the variability of a range of life outcomes and measures of adaptation (Buer Christensen et al., 2020; Cruitt et al., 2019), whereas in our study the number of elevated maladaptive traits accounts for 27-38% of the variation in caseness and multidimensional distance metrics account for 33-47%. This is not unexpected, as pathological traits have been shown before to be powerful predictors of maladaptation by themselves. For example, neuroticism is the essence of most psychopathology, daily life problems, and unhappiness (Kotov et al., 2010; Vall et al., 2015), antagonism is robustly associated to antisocial behavior, aggression, accidents, and drug use (Lynam & Miller, 2019), and disinhibition not only underlies numerous disorders but complicates the course of many others (Mullins-Sweat et al., 2019).

Even so, our latest finding is that are not individual personality traits that work the best. Although identity problems, depressivity-anhedonia, and self-harming behaviors are particularly robust predictors of mental problems, profile-level parameters outperform them as a whole. Particularly, Mahalanobis distance between each individual profile and the centroid of the general population outdoes all other metrics —including the g-PD— by being able to correctly classify as clinical or nonclinical around 76-78% of the subjects. This is relevant to the study of individual differences at large, as research dealing with multidimensional constellations of traits or symptoms can misconstrue between-group effect sizes if suboptimal metrics are used (Del Giudice et al., 2012). However, it is also relevant to diagnostic decisions in the newer dimensional taxonomies of PD, whose maladaptive traits overlap substantially (Morey et al., 2022; Ringwald et al., 2021).

Overlap is generally assumed to reflect the existence of a single underlying dimension that is common to all PDs and is indicative of dysfunction (i.e. the g-PD; Morey et al., 2013), whereas non-shared variance is grouped into specific factors. By contrast, Mahalanobis distance isolates the axis of variation that best discriminates between community and clinical subjects by discounting overlap, that is, by incorporating only trait variance that provides non-shared additional information on group differences (Del Giudice, 2021). Our results depict it as a promising complementary or alternative approach to diagnosis in multivariate domains.

As a limitation, it must be noted that both the DAPP-BQ and the PID-5 are self-reported measures. In future studies, interview-based assessment of PD traits would help to obtain a fuller and more generalizable picture. Another caveat is that caseness is only one among many possible maladaptation criteria. In the absence of an undisputed gold standard for PD (Zimmerman et al., 2018), the fact that traits lead to the development of mental problems can be deemed a relevant criterion (Leising & Zimmermann, 2011). However, belonging to a clinical population does not equate with having a PD, and a disproportionate weight may have been given to traits reflecting anxious-depressive features. Furthermore, plenty other criteria —the endless work, financial, relational, and health problems that PDs chronically drag along with them— would have led to different results and remain to be studied (Leising & Zimmermann, 2011). Even more, distinct personalities are known to result in different kinds of adversities (Clark & Ro, 2014; Vall et al., 2015), so that not all outcomes are appropriate to discern all PDs. Defining disorder is still a major challenge in the ongoing development of evidence-based diagnostic systems.

In sum, we find that intense maladaptive traits are the norm rather than the exception in the general population. This urges caution not to mistake unideal for disordered personalities when we use dimensional systems. It also calls for the pursuit of empirically-based diagnostic thresholds which are able to predict relevant clinical criteria. In this effort, personality trait profiles are powerful predictors of maladaptation by themselves and deserve further consideration than they have received so far. Not less important, the multivariate spaces generated by dimensional classificatory systems operate according to their own particular logic and will require proper metrics.

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Electronic Supplementary Material

ESM1. Contains variance-covariance matrices for calculating Mahalanobis distances (Tables S1-S2) and supplementary results for trait- and profile-level predictors (Tables S3-S6).