ORIGINAL ARTICLE

Latent classes of maladaptive personality traits exhibit differences in social processing

Lauren Hanegraaf¹

¹Turner Institute for Brain and Mental Health, Monash University, Clayton, Victoria, Australia

²Cognition and Philosophy Lab, Philosophy Department, Monash University, Clayton, Victoria, Australia

Correspondence

Lauren Hanegraaf, Turner Institute for Brain and Mental Health, Monash University, Clayton, VIC, Australia. Email: lauren.hanegraaf@monash.edu

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Jakob Hohwy² Antonio Verdejo-Garcia¹

Abstract

Objective: Social processing (SP) deficits manifest across numerous mental disorders. However, this research has been plagued by heterogeneity and a piecemeal approach whereby skills are examined in isolation rather than as part of an integrated cognitive system. Here, we combined two dimensional frameworks of psychopathology to address these limitations.

Method: We utilized the Alternative Model for Personality Disorders (AMPD) to distill trait-related heterogeneity within a community sample (n = 200), and the Research Domain Criteria (RDoC) 'Systems for Social Processes' to comprehensively assess SP. We first applied latent class analyses (LCA) to derive AMPDbased groups and subsequently contrasted the performance of these groups on a SP test battery that we developed to align with the RDoC SP constructs.

Results: Our LCA yielded four distinct subgroups. The recognizable trait profiles and psychopathological symptoms of these classes suggested they were clinically meaningful. The subgroups differed in their SP profiles: one displayed deficits regarding the self, a second displayed deficits in understanding others, a third displayed more severe deficits including affiliation problems, whilst the fourth showed normal performance.

Conclusions: Our results support the link between clusters of maladaptive personality traits and distinctive profiles of SP deficits, which may inform research on disorders involving SP dysfunctions.

KEYWORDS

dimensional, personality, social cognition, social processing, transdiagnostic

1 **INTRODUCTION**

Social processing (SP) encompasses the set of cognitive processes underlying the ability to perceive, understand, and respond to others (Pinkham et al., 2014). Disruptions in SP occur across a wide range of psychiatric,

neurodevelopmental, and neurodegenerative disorders, and play a key role in the etiology and maintenance of social dysfunction (Kennedy & Adolphs, 2012; Thoma et al., 2013). There is evidence that similar SP deficits occur across psychiatric disorders, suggesting they may be an underlying cognitive phenotype (Cotter et al., 2018). However,

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progress in this field has been significantly limited by the striking heterogeneity in SP dysfunction within diagnostic categories (Cotter et al., 2018; Gonzalez-Gadea et al., 2013; Samamé et al., 2015), and in participants without psychiatric disorders who are classified as 'healthy controls' (Etchepare et al., 2019). This heterogeneity highlights a clear need to identify factors that underlie differences in SP.

There is a growing body of evidence indicating that inter-individual differences in maladaptive personality traits may be linked to differences in SP in both clinical (e.g., Hanegraaf et al., 2020) and nonclinical populations (e.g., Calder et al., 2011). Maladaptive personality traits have also been shown to explain the variance in numerous social outcomes (Gleason et al., 2014) and have been highlighted as intermediate markers of psychiatric disorders in current dimensional nosological classification systems (Bornstein, 2018). One of the most well-established of these systems is the American Psychiatric Association (APA) Diagnostic and Statistical Manual (DSM-5) Alternative Model for Personality Disorders (AMPD), which emphasizes the link between maladaptive traits (Criterion B) and self and interpersonal functioning (Criterion A; Bornstein, 2018; Widiger et al., 2019). Criterion B of the AMPD comprises 25 maladaptive trait facets that are organized into five higher order domains (Negative Affect, Detachment, Disinhibition, Antagonism, and Psychoticism) which are proposed to vary along a dimension within the normal population, with psychiatric disorders representing the extreme tail end of the distribution.

This approach of considering psychopathology in terms of dysfunction along a dimension aligns with the paradigm shift toward transdiagnostic research, and the emerging interest in identifying phenotypes that underlie cognitive and behavioral dysfunction. A framework for dimensional research was developed by the National Institute of Mental Health, titled the Research Domain Criteria (RDoC; Kose & Cetin, 2017). The RDoC has operationalized a set of biologically meaningful constructs that underpin SP, outlined in the domain 'Systems for Social Processes'. Within this framework, SP dysfunction is conceptualized along a dimension from normal information processing to severe dysfunction (Kose & Cetin, 2017). It is worth clarifying that this operationalization of SP dysfunction differs from normative SP biases (e.g., heuristics or stereotypes) which are not indicators of psychopathology. Although historically, SP research has focused primarily on areas such as theory of mind (i.e., understanding the intentions of others) and emotion processing (i.e., the ability to interpret others' emotions), the RDoC 'Systems for Social Processes' domain advocates for comprehensive research across a broader range of four key SP constructs: Attachment and Affiliation, Social Communication, Perception and Understanding of the Self, and Perception and Understanding of Others.

Notably, the structure of the RDoC 'Systems for Social Processes' and Criterion A of the AMPD share a high degree of resemblance. Analogous to Criterion A, the 'Systems for Social Processes' domain outlines constructs that encompass perception of the self and others, mentalization, and responses to social stimuli (Waugh et al., 2017). Importantly, research that links the AMPD and the RDoC has the potential to address the limitations posed by either framework alone. Although the RDoC system presents an opportunity to advance the understanding of cognitive processes relevant to SP, a significant criticism of this system is that it lacks comprehensive and detailed coverage of clinical phenotypes (Kotov et al., 2017). Conversely, nosological classification systems such as the AMPD are limited by their sole focus on clinical manifestations, which have no clear link to biological and behavioral constructs (Kotov et al., 2017). Thus, the integration of these frameworks would not only contribute to the clinical relevance of the RDoC, but also provide key insights into the neurobiological underpinnings of the dimensions outlined within the AMPD.

In summary, maladaptive personality traits have informed the latest dimensional psychopathology classification systems and have been linked to inter-individual differences in SP (Hanegraaf et al., 2020; Waugh et al., 2017). However, it is not yet known whether latent phenotypes of maladaptive traits manifest in the normal population, and if so, whether they differ in their SP. Therefore, we aimed to investigate whether AMPD-based trait scores can yield subgroups of individuals within the normal population that exhibit differences in SP. Exploring this initially within a normal population permits subsequent exploration of the extent to which aspects of SP deviate from normality in clinical conditions (Cuthbert, 2014), and could inform future research aiming to find new ways of identifying and targeting psychopathology. We used a statistical clustering technique (latent class analysis; LCA) to determine what trait sub-groups exist, and subsequently compared the performance of these sub-groups on a comprehensive battery of SP tasks guided by the RDoC 'Systems for Social Processes' domain. We hypothesised that LCA-driven personality subtypes would exhibit significant performance differences on SP measures.

2 | METHODS

2.1 | Participants

A total of 283 participants were recruited from Amazon Mechanical Turk (MTurk) via the TurkPrime online platform (Litman et al., 2017). MTurk is an online crowdsourcing platform that facilitates the recruitment of community-based participants to research studies (Kees et al., 2017). Participants recruited from MTurk are more demographically diverse, geographically dispersed, and have been shown to perform better across measures of data quality in comparison to other samples (e.g., students, professional panels; Kees et al., 2017). Based on the recommendations of Robinson et al. (2019), we adapted our MTurk recruitment procedure to ensure data quality. Namely, only workers who had completed >100 tasks with a >90% approval rate were invited to participate. We additionally excluded the top 1% of MTurk workers (who complete 21% of tasks) to decrease the likelihood of recruiting non-naïve participants (Chandler et al., 2019).

We chose to have minimal eligibility criteria, to ensure our sample was broadly representative of the normal population. Participants were required to be between 18 and 50 years and speak English as a preferred language. Self-reported history of loss of consciousness or hospitalization due to head injury, current diagnosis of bipolar disorder and schizophrenia (given the cognitive underpinnings of these disorders), and neurological and other conditions that impacted the central nervous system (including HIV, seizure disorders, stroke and multiple sclerosis) were exclusion criteria.

Eighty-three participants were excluded from the study due to: (1) failing to meet prescribed eligibility criteria (n = 60), (2) failing to complete the survey (n = 7), or (3) failing to pass quality control checks (n = 16, see Supporting Information 1 for a description of quality control checks). We continued recruiting until we achieved our sample size goal (n = 200), which is comparable to those reported in previous research conducting LCA (Albein-Urios et al., 2014; Hori et al., 2017). The final sample comprised 55.0% females and 45.0% males (mean age = 33.86, SD = 6.97), and 31 participants (15.5%) reported a current psychiatric diagnosis (see Supporting Information 2 Table S5). The demographics of these 200 participants were broadly representative of the adult US population (see Supporting Information 2 for more detailed information).

2.2 Measures

2.2.1 | Personality trait measure for the latent classes

Trait domain scores derived from the Personality Inventory for the DSM-5 – Short Form (PID-5-SF) were used as predictors in the latent class analysis. The PID-5-SF (American Psychiatric Association, 2013; Maples et al., 2015) is a 100-item abbreviated version of the original 220-item PID-5, and measures 25 personality facets underlying the five trait domains identified in the DSM-5 AMPD (i.e., Negative Affect, Detachment, Disinhibition, Antagonism, and Psychoticism). Each facet is assessed with four items using a Likert response format, with scores ranging from 0 (very false or often false) to 3 (very true to often true). Domain scores were calculated utilizing the algorithm provided by the APA, where scores from the three facets that have the strongest factor loadings on each domain are averaged (Krueger et al., 2013), and higher scores represent greater trait presence. The PID-5 was developed by the APA to assess Criterion B of the AMPD, thus it is a useful measure to directly assess the DSM-5 trait model (Krueger & Markon, 2014). It displays good internal consistency (Cronbach's $\alpha = .89$ to .91), and a highly similar factor structure (congruency coefficients = 0.93 to 0.99) and identical criterion validity to the original 220-item PID-5 form (Thimm et al., 2016).

2.2.2 | Online SP battery

We built a suite of five online tasks that comprehensively assessed each of the constructs of the 'Systems for Social Processes' domain in the RDoC framework (see Table 1). One task was chosen for each construct, with the exception of the 'Social Communication' construct where two measures were chosen: one that assessed "Reception of Facial Communication", and one that assessed "Reception of Non-Facial Communication". All SP tasks were either listed as a paradigm or operationalized the behaviour descriptors in the relevant construct of the RDoC matrix. A decision on the task to be used for each construct was made based on the ability to be administered online, length, and ecological validity. Except for the Biological Motion Task, all measures were established tasks which were requested from the authors who developed them and adapted to the study setting. The procedure for creating and validating the Biological Motion Task is described in Supporting Information 1.

2.2.3 | Demographic and clinical selfreport measures

We used an internally developed survey to collect sociodemographic information (i.e., age, gender, psychiatric diagnoses). Severity of depression, anxiety, and stress were assessed using the Depression Anxiety Stress Scale – 21 item version (DASS-21; Lovibond & Lovibond, 1995). The Drug Use Disorders Identification Test (DUDIT; Berman et al., 2005) was administered to collect information about drug use and related consequences over the past 12 months. These clinical variables were included as they represent prevalent manifestations of psychopathology in community samples.

TABLE 1 Description of social processing tasks and corresponding 'systems for social processes' constructs

RDoC construct/subconstruct	Instrument used	Description	References
Affiliation and Attachment	Sense of Commitment Paradigm	Participants are presented with a vignette describing a situation in which they are engaged in a joint commitment with a neighbor. The vignette is followed by one of two videos which display either a low or high degree of coordination. Participants are then asked four questions rated on 5-point Likert scales: (1) perceived commitment: how long they would expect the neighbour to continue helping; (2) gratitude: how they would feel if the neighbor keeps helping; (3) annoyance: how annoyed they would feel about a violation of the commitment; (4) withdrawal: how likely they would be to help the neighbour in the future if they violated the commitment. Higher scores indicate greater endorsement of the variable	Michael et al. (2016)
Social Communication/Reception of Facial Communication	ER-40	Presents participants with 40 photographs of faces which express one of five basic emotions (happiness, sadness, anger, fear, and neutral), and asks them to identify the emotion. An automated scoring program provides averaged accuracy percentages (0%– 100%); higher accuracies indicate better facial affect recognition	Kohler et al. (2005)
Social Communication/Reception of Non-Facial Communication	Emotional Biological Motion Task	Assesses participants' ability to detect emotion in biological motion using 5–10 s videos of point-light walkers. After each video, participants rate the emotional valence displayed in the video on a 7-point scale (negative to positive), and their confidence in their rating (11-point scale from 0%–100%)	Kaletsch et al. (2014), Manera et al. (2010) and Piwek et al., (2016)
Perception and Understanding of Self/Self-Knowledge	Self-Referential Memory Paradigm	An online measure of the self-reference effect, which presents participants with encoding questions related to 30 adjectives (10 self-referential questions, 10 semantic questions, 10 structural questions), and asks them to recall these adjectives following a distraction task. For the self- reference effect, the % of adjectives recalled for each question type is the DV. Key DVs for self-concept are the total number of words, and the % of negative and positive words self-attributed	Bentley et al. (2017), with additional variables for self- concept adapted from Auerbach et al. (2016)

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TABLE 1 (Continued)

RDoC construct/subconstruct	Instrument used	Description	References
Perception and Understanding of Others/Understanding Mental States	MASC-MC	Comprises a 15-min dubbed movie depicting four interacting characters. The movie is paused at 45 points; participants are presented with four possible answers and asked to click on the answer that correctly describes what the characters are thinking or feeling. A sum score of correct responses is calculated (range = 0 to 45); higher scores indicate greater mentalizing ability. Further, a sum score of three error types (hypermentalizing, hypomentalizing, no theory of mind) is provided	Dziobek et al. (2006)

Abbreviations: ER-40, Penn emotion recognition task; MASC-MC, movie for the assessment of social cognition - multiple choice.

2.3 | Experimental design and procedure

This study adopted a cross-sectional online survey design, which was implemented through Qualtrics and Inquisit by Millisecond. The survey took approximately 60-90 min, and participants were instructed to complete it in one sitting. The length of this survey is comparable to that of previous MTurk studies that produced highly reliable data (Verdejo-Garcia et al., 2021) and we included rigorous methods to ensure data quality (see Supporting Information 1). Additionally, to promote vigilance over the duration of the survey (based on Helton & Russell, 2015) prompts were given to take 5-min breaks in between SP tasks. Further, the order of SP tasks was chosen to minimize performance effects: alternating difficulty (easy vs. hard) and input (visual vs. verbal). At completion of the survey, participants were reimbursed through TurkPrime at the standard rate of \$9.00 (USD; \$0.10 per min). The Monash University and Eastern Health Human Research Ethics Committees approved the study and all participants provided informed consent. Data were collected between October 22nd 2019 and January 3rd 2020. The analysis and reporting of this study were performed with guidance from the Strengthening the Reporting of Observational Studies in Epidemiology statement checklist (Von Elm et al., 2007).

2.4 | Data analysis

Our data analysis strategy comprised two sequential steps. First, we conducted LCA to derive subgroups (i.e., latent classes) that exhibited different maladaptive trait profiles. In contrast to the typical diagnostic cut-off classifications (e.g., clinical group vs. controls) of individuals used in research, LCA provides an empirical, data-driven method of classifying individuals, allowing for key items to be differentially influential in obtaining the classifications (Bornovalova et al., 2010). Secondly, we compared these subgroups on our battery of SP tasks. Support for our hypothesis would be indicated by the presence of two or more subgroups that exhibited significant differences across SP tasks and variables.

2.4.1 | Step 1: Latent class analysis

Latent class (LC) models were fit to the domain scores on the PID-5 using the statistical modeling software Mplus (Muthén & Muthén, 2009). The estimation of each model was conducted with 100 random sets of start values and 20 final stage optimizations, to ensure that the models converged on local rather than global solutions (Nylund et al., 2007). For each model, we utilized both of the typical methods for determining the number of classes: likelihoodbased tests and Information Criterion. The bootstrap likelihood ratio test (BLRT) has been demonstrated to have the best accuracy for correctly identifying the true number of classes, and has the most consistent power across all sample sizes (Nylund et al., 2007). Therefore, for each model, the BLRT was conducted ($\alpha = .05$) with 5000 bootstrapped draws (McLachlan et al., 2019); where p < .05 indicated that the k-class model provided a better fit than a (k - 1)model (Bornovalova et al., 2010). In addition, the Bayesian Information Criterion (BIC) was used to evaluate model fit, where smaller values indicate better model fit. This was preferred over other information criteria, as the BIC has been found to most consistently identify the correct model for continuous LCA models (Nylund et al., 2007). Each LCA model yields two types of parameter estimates that inform accurate class membership estimation:

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class membership probabilities, which reflects the probability that an individual belongs to each class, and itemresponse probabilities, which facilitates interpretation by indicating the probability of endorsement of a given characteristic (i.e., trait) for individuals in a given class (Porcu & Giambona, 2017). Item-response probabilities were additionally inspected to create descriptive labels for the classes. Due to previous research indicating potential sex differences in personality traits (Schmitt et al., 2008), we also explored whether latent classes were being driven by response style differences between sexes by using the method described in Bornovalova et al. (2010).

2.4.2 | Step 2: Comparison of group on SP and clinical measures

Group comparison analyses were conducted using SPSS Version 27.0 (IBM Corp, 2020) and R (R Core Team, 2013). Due to group size differences and violations of normality and homogeneity of variance, we performed group comparisons using the permuted Wald-Type statistic Q_n (WTPS; Pauly et al., 2015) which are implemented in the R package "GFD" (version 0.2.4; Friedrich et al., 2017). Significant interactions and group differences (p < .05) were explored using a series of two-way comparisons with the WTPS. Multiple testing correction was applied using the Benjamin-Hochberg procedure, with a stringent false discovery rate of q = 0.05. Adjusted p values (p_{adj}) are reported in addition to original *p* values. For brevity, only the results relevant to our hypothesis (i.e., group main effects and interactions) are reported; see Supporting Information 1 Tables S2-S4 for the full results. Due to violations of normality and homogeneity, group differences on clinical measures (DASS and DUDIT) were also explored utilizing the WTPS approach described above.

3 | RESULTS

3.1 | Latent class analysis

Table 2 contains the model fit information for the LCA models. The results of the bootstrap LRT and the BIC indicated that the four-class model provides statistically significantly better fit than the three-class model. The five-class model was unable to be uniquely identified due to insufficient degrees of freedom (class 5 n = 1; Abar & Loken, 2012), indicating too many classes were being extracted (Geiser, 2012). Therefore, the four-class solution had the best fit, which also demonstrated high classification accuracy (87.30%). Although there was a direct effect of sex on the probability of falling into specific classes,

TABLE 2 Fit statistics for latent class models

		BLRT	
Model	Log-likelihood	р	BIC
1 class	-874.11		1801.20
2 class	-742.63	<.001	1570.03
3 class	-699.17	<.001	1514.90
4 class	-673.56	<.001	1495.46

Note: Smaller negative log-likelihood and BIC values indicate better model fit.

Abbreviations: BIC, Bayesian Information Criterion; BLRT, Bootstrapped Likelihood Ratio Test.

the model that included sex as a covariate did not provide a statistically better fit according to information criteria (BIC = 1781.65). Thus, the initial four-class model without sex was retained.

Figure 1 plots the estimated marginal means (EMMs) for each of the trait domains on the PID-5-SF and reveals an interpretable structure for each of the latent classes (LC). For the sake of clarity, we have given each of the LCs a proxy label based on their trait compositions. LC 1 ("low psychopathology" group) was the largest class in the analysis (58% of the sample) and was characterized by low scores across all maladaptive personality trait domains. In contrast, LC 4 (7.5%; "high psychopathology" group) displayed high levels of all maladaptive personality traits. LC 2 and LC 3 were medium maladaptive personality trait classes, with comparable sizes (14% and 20.5%, respectively). The two medium groups significantly differed across all trait domains except for disinhibition. LC 3 ("internalizing/detached" group) was characterized by higher detachment in comparison to LC 2. Conversely, LC 2 displayed higher levels of negative affect, antagonism, and psychoticism ("externalizing/antisocial" group) in comparison to LC 3.

3.2 Demographics and clinical differences of the latent classes

Results of group comparisons on demographic and clinical measures are presented in Table 3. Although there was a significant main effect of age, individual group comparisons were not significant. Group comparisons for gender and presence of psychiatric disorders were also not significant.

The "internalizing/detached" and "externalizing/antisocial" groups displayed elevated levels of depression, anxiety, and stress in comparison to the "low psychopathology" group. The two medium groups differed on levels of depression: the "internalizing/detached" group were significantly more depressed than the "externalizing/antisocial" group. Conversely, the "externalizing/antisocial"

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group displayed significantly higher levels of drug use and anxiety. The "high psychopathology" group were characterized by high levels across all clinical measures except drug use; they displayed high levels of depression, anxiety and stress (Table 3).

3.3 | Class-related differences in SP

Figure 2 presents group differences across each of the SP measures.

3.3.1 | Attachment and affiliation: Sense of commitment

There was a significant main effect of group for 'Annoyance': the "high psychopathology" group were significantly more annoyed at violations of commitment than all other groups ($Q_n s[1] > 7.167 \text{ ps} < .015$, $ps_{adj} < .05$; see Figure 1). There was no significant group × condition interaction, and therefore insufficient evidence to suggest that this effect differed based on the degree of coordination. There were no significant main effects or interactions for the remaining variables (Perceived Commitment, Gratitude, Withdrawal; see Supporting Information 1 Table S2).

3.3.2 | Reception of facial communication: Emotion recognition task

There was no significant main effect of group $(Q_n [3] = 6.65, p = .09)$ or group × emotion interaction $(Q_n [12] = 9.15, p = .75)$, suggesting the groups did not exhibit differences in their ability to identify facial emotions.

3.3.3 | Reception of non-facial communication: Emotional body movements

Valence

There was a significant main effect of group which was characterized by a significant group × emotion interaction: the "externalizing/antisocial" group rated negative videos as significantly more positive than the "low psychopathology" group ($Q_n[1] = 7.39$, p = .01, $p_{adj} = .04$). No other group interactions were significant after multiple comparisons corrections (see Supporting Information 1 Table S3).

Confidence

There was a significant main effect of group: in comparison to the "low psychopathology" group, the "internalizing/detached": $(Q_n [1] = 22.53, p < .001, p_{adj} < .001)$ and "externalizing/antisocial" groups $(Q_n [1] = 48.23, p < .001, p_{adj} < .001)$ were less confident in their ratings of valence. The "externalizing/antisocial" group was also less confident in their ratings than the "high psychopathology" group $(Q_n [1] = 5.24, p < .001, p_{adj} < .01)$. No group interactions were significant, indicating that group confidence ratings did not differ based on emotion (negative, positive), context (monadic, dyadic) or difficulty (easy, hard).

3.3.4 | Perception and understanding of self: Self-referential memory paradigm

Self-concept

There was a significant group × valence interaction (Q_n [3] = 222.88, p < .001): the "low psychopathology" group selfattributed significantly more positive words than the "internalizing/detached" (Q_n [1] = 32.68, p < .001, $p_{adj} < .001$) and "high psychopathology" groups (Q_n [1] = 9.73, p = .01, $p_{adj} = .04$). Further, the "externalizing/antisocial" group



FIGURE 1 Trait composition of the latent classes. LC, latent class

TABLE 3	Descriptive statistics	and group differences	s on demographic and o	clinical variables
	1			

	LP (<i>n</i> = 116)		EXT $(n = 28)$		INT (<i>n</i> = 41)		HP (<i>n</i> = 15)			
	EMM	SEM	EMM	SEM	EMM	SEM	EMM	SEM	р	Post-hoc
Age	34.98	6.37	31.18	7.82	33.32	7.44	31.67	7.17	.03 ^a	N.S.
Gender (% Female)	54.30		75.00		51.20		33.30		.054 ^c	
PID-5 Traits										
Negative Affect	0.55	0.44	1.52	0.60	1.17	0.56	1.74	0.41	<.001 ^a	EXT, $HP > INT > LP^{a}$
Detachment	0.44	0.42	0.72	0.39	1.74	0.48	1.59	0.46	<.001 ^a	INT, $HP > EXT > LP^a$
Antagonism	0.30	0.38	0.75	0.47	0.40	0.41	1.48	0.51	<.001 ^a	$HP > EXT > INT, LP^{a}$
Disinhibition	0.27	0.30	0.99	0.41	0.73	0.43	1.61	0.43	<.001 ^a	$HP > EXT, INT > LP^{a}$
Psychoticism	0.23	0.26	1.10	0.38	0.56	0.27	1.61	0.39	<.001 ^a	$HP > EXT > INT > LP^{a}$
DASS										
Depression	4.19	7.04	12.14	8.16	19.17	9.92	25.87	12.20	<.001 ^b	$\mathrm{HP} > \mathrm{INT} > \mathrm{EXT} > \mathrm{LP}^{\mathrm{b}}$
Anxiety	2.29	3.89	10.07	7.88	6.15	6.86	18.40	10.06	<.001 ^b	$HP > EXT > INT > LP^{b}$
Stress	5.24	6.50	16.07	7.95	12.83	7.17	20.80	11.46	<.001 ^b	$HP > EXT, INT > LP^{b}$
DUDIT	1.26	4.07	3.61	4.52	1.68	4.37	10.33	13.94	<.001 ^b	$EXT > LP$, INT, HP^b
Psychiatric diagnosis (%)	12.10		17.90		26.80		6.70		.11 ^c	

Note: Estimated marginal means were reported in consideration of differences in group sizes.

Abbreviations: DASS, depression anxiety and stress scale; DUDIT, drug use disorders identification test; EMM, estimated marginal means; EXT, externalizing/ antisocial group; HP, high psychopathology group; INT, internalizing/detached group; LP, low psychopathology group; N.S., not significant; PID-5, personality inventory for the DSM-5.

^a*p* values with next to them refer to results of between group ANOVA.

^bRefers to Wald Type Permuted Statistic.

^cRefers to chi-squared test. Post-hoc comparisons with ^a refer to results of follow-up Games Howell pairwise comparisons, ^b refers to Wald Type Permuted Statistic two-way comparisons.

self-attributed significantly more positive words than the "internalizing/detached" group (Q_n [1] = 11.86, p < .001, $p_{adj} = .004$). In contrast, the "internalizing/detached" group self-attributed significantly more negative words in comparison to the "low psychopathology" group (Q_n [1] = 14.15, p < .001, $p_{adj} = .006$), indicating they displayed a more negative and less positive self-concept. Pairwise comparisons for the total number of words self-attributed revealed that the "internalizing/detached" group self-attributed significantly less words than the "low psychopathology" group (Q_n [1] = 14.15, p = .01, $p_{adj} = .04$), suggesting they also had a less complex self-concept.

Self-reference effect

No group or group interactions were significant; the groups did not differ based on the number of words recalled or the types of words recalled. Results of this analysis are presented in Supporting Information 1 Table S4.

3.3.5 | Perception and understanding of others: Mentalizing

There was a significant main effect of group $(Q_n[3] = 17.26, p = .004)$: in comparison to the "low psychopathology

group", the "externalizing/antisocial" (Q_n [1] = 7.47, p = .008, p_{adj} = .04), and "high psychopathology" groups (Q_n [1] = 8.52, p = .006, p_{adj} = .03) made more total errors, indicating that they were less accurate at identifying the mental state of others. Further, the "internalizing/detached" group also made fewer total errors than the "high psychopathology" (Q_n (1) = 8.11, p = .006, p_{adj} = .03) and "externalizing/antisocial" groups (Q_n (1) = 6.05, p = .014, p_{adj} = .049). The group × error type interaction was not significant (Q_n (6) = 10.14, p = .13) suggesting the groups did not differ in the types of errors made.

4 | DISCUSSION

We tested the link between personality-based phenotypes and SP in a community-based sample, by combining two dimensional frameworks of psychopathology—the AMPD and the RDoC. Using the AMPD, we identified four distinct latent classes of maladaptive traits in a community sample. The severity gradation, recognizable trait profiles, and psychopathological symptoms characteristic of these trait classes suggested they were clinically meaningful and provide support for an integrated categoricaldimensional approach to psychopathology (Borsboom



FIGURE 2 Results of group comparisons on social processing measures. (a) Attachment and affiliation: sense of commitment paradigm; (b) Reception of facial communication: Penn emotion recognition task; (c) reception of non-facial communication: biological motion task; (d) perception and understanding of self: self-referential memory paradigm; (e) perception and understanding of others: movie for the assessment of social cognition. MASC, Movie for the Assessment of Social Cognition. * $p_{adj} < .05$, ** $p_{adj} < .01$, *** $p_{adj} < .001$

623

et al., 2016). Further, the trait-derived classes enabled us to segregate performance across key SP constructs listed in the RDoC 'Systems for Social Processes' domain, providing evidence for consilience between these two dimensional models. Indeed, the trait-derived classes yielded (1) severity-related effects on specific SP constructs, and (2) a dissociation between externalizing/antisocial and internalizing/detached subgroups across SP constructs.

Our latent class analysis revealed strong evidence for four underlying classes of maladaptive personality traits. Two of these classes appeared to represent the upper and lower end of a severity continuum: one exhibited low endorsement across all maladaptive personality traits, and one exhibited high endorsement across all maladaptive personality trait domains. Further, two 'middle' classes emerged that displayed distinctive and recognizable trait profiles: one exhibited a predominantly antisocial/externalizing trait profile (i.e., high levels of antagonism, disinhibition; Mullins-Sweatt et al., 2019), whilst the other exhibited a predominantly detached/internalizing profile (i.e., high levels of detachment and negative affect; Sellbom et al., 2020). Notably, these trait profiles were broadly consistent with the internalizing/externalizing structure that is well-replicated in two-factor trait models of psychopathology (Ormel et al., 2005; Widiger et al., 2019). The only exception to this was the high levels of negative affect endorsed by the "externalizing/antisocial" group (typically considered an internalizing trait). Although negative affect is not generally considered a defining externalizing trait, symptoms of anxiety and distress (as captured by this domain) commonly manifest in externalizing disorders (e.g., Galbraith et al., 2014; Gnanavel et al., 2019; Goodwin & Hamilton, 2003), and there is some evidence that suggests it underlies both externalizing and internalizing aspects of psychopathology (Mikolajewski et al., 2013). Overall, the identification of these subgroups suggests that meaningful maladaptive personality clusters, similar to those described in clinical populations, manifest in a community sample as proposed by dimensional models (Kotov et al., 2017).

Interestingly, the psychopathological characteristics of these trait-derived subgroups were associated with their severity and distinct trait profiles. Along the severity continuum, LCs with higher maladaptive trait endorsement displayed a higher presence of clinical symptoms (i.e., the "low psychopathology" group displayed low scores across measures of clinical symptoms, and the "high psychopathology" group displayed elevated scores across these measures). Further, the differences between the two 'medium' groups were consistent with their externalizing/ internalizing profiles. Namely, the "externalizing/antisocial" group had higher levels of drug use and anxiety (Acharya & Dolan, 2012; Goodwin & Hamilton, 2003), whilst the "internalizing/detached" group had higher levels of depression (Sanders et al., 1999). Although preliminary, these findings provide important support for the clinical relevance of these latent classes and the trait model of psychopathology.

The trait-derived classes were also associated with distinctive and interpretable profiles of SP. Indeed, our data suggested there was both an effect of severity (i.e., the 'low' trait subgroup exhibited no SP dysfunction, the 'high' trait subgroup exhibited the most widespread SP dysfunction), and an effect of types of traits endorsed, as indicated by the clear dissociation between the "externalizing/antisocial" and "internalizing/detached" subgroups. Specifically, the deficits revealed in mental state discrimination and judging the emotional valence of body movements suggests that the "externalizing/antisocial" subgroup exhibited a primary impairment of social inference (Molapour et al., 2021). It is also noteworthy that this SP profile was also broadly in line with expectations based on the externalizing and antisocial trait literature. Namely, antisocial traits (i.e., antagonism, disinhibition) have been linked with impairments in mental state discrimination and empathy, which have been proposed as an underlying factor of externalizing behaviors such as increased hostility and aggression (Clements & Schumacher, 2010; Song et al., 2016; Yaghoub Zadeh et al., 2007).

In contrast, the "internalizing/detached" subgroup displayed a primary self-representation impairment, characterized by a negative self-concept and reduced confidence despite displaying no deficits in their ratings of emotional valence. Confidence about one's own cognition is a core metacognitive ability, and is fundamental for the regulation of subjective social experiences, social learning, and internal representations of the self (Molapour et al., 2021; Wu et al., 2020). The link between metacognition (i.e., confidence ratings) and self-concept has been proposed to be explained by a tendency toward a constant level of self-appraisal (Dapp & Roebers, 2021). Thus, this pattern could be interpreted as exhibiting a general tendency toward negatively biased self-appraisals. This interpretation also aligns with the high levels of depressive symptoms endorsed by this group, as it has been well-established that individuals with clinical and subclinical depressive symptoms display a global negative 'self' bias (Iijima et al., 2017). Again, this pattern of SP also aligned with expectations based on the internalizing trait profile displayed by this group: internalizing traits are commonly associated with poor self-esteem (Creemers et al., 2013) and have been linked to a negative self-concept (Ybrandt, 2008).

Interestingly, the "high psychopathology group", who endorsed high levels of both externalizing and internalizing traits, exhibited impairments across both social inference and self-valuation, as well as an additional

impairment in their responses to violations of perceived commitment. This latter result indicates that in addition to trait profile differences in SP, there may also be severity-related effects on specific elements of SP such as Attachment and Affiliation. Of note is that this construct requires an ability to detect and attend to social cues and relies on social learning and memory (per RDoC matrix description; Insel et al., 2010); thus, it is possible that this severity-related effect is secondary to the associated impairment across a wide range of SP constructs. Consistent with this explanation, the discrepancy between low accuracy and high confidence displayed by the "high psychopathology" group when viewing emotional body movements suggests they exhibit biased metacognition, which as previously noted plays an important role in the regulation of social learning (Wu et al., 2020). Although the 'low accuracy' (i.e., negative bias) finding was not significant after multiple comparisons correction, this discrepancy (i.e., confidence inconsistent with objective performance) resembles what has been obtained through 'calibration' studies (e.g., Moritz et al., 2014). Problems calibrating confidence have been demonstrated as a risk factor for paranoia, emotional, and behavioral problems (Moritz et al., 2014), as inaccurate calibration of confidence may hinder further reasoning processes that would help correct false social judgments and attenuate further social conflicts (Schilling et al., 2012). Since poor confidence calibrations appear to be a marker of ongoing severity, assessment of this may provide an important opportunity for interventions aiming to increase metacognitive awareness (e.g., metacognitive training; Moritz et al., 2010). Alternatively, it is possible that the high levels of antagonism endorsed by the "high psychopathology group" underlie their heightened annoyance response to violations of perceived commitment, given this trait has been previously associated with a tendency toward hostile or angry responses (Chester & West, 2020).

Altogether, the identification of these recognizable trait subgroups that exhibit distinct and valid SP profiles provides critical evidence for the consilience between the RDoC 'Systems for Social Processes' domain and the AMPD. This coalescence represents a step toward redressing the limitations of each framework: the RDoC lacks a clear link to clinically meaningful dimensions and the neurocognitive bases of AMPD remain unclear (Kotov et al., 2017). Importantly, our results provide preliminary support for the clinical relevance of the RDoC SP constructs, and the neurobehavioral relevance of the AMPD traits. Such information is essential for both the refinement of the RDoC 'Systems for Social Processes' domain, and the validation of trait dimensions outlined in the AMPD.

The present study has limitations which warrant consideration. Firstly, although we utilized a high number of permutations in our LCA, cross-validation of our class structure in independent or larger samples would lend further validity to the stability of our findings. As is a limitation with all exploratory data reduction approaches such as LCA, we acknowledge the possibility that alternative class structures may emerge in other samples. For example, our "externalizing/antisocial" subgroup also exhibited thought disordered traits, which has been proposed as a separate third underlying trait factor in other dimensional models (i.e., HiTOP; Kotov et al., 2017). For ease of reading, we assigned proxy labels for our LCs based on their broad trait structures. However, we recognize that other interpretations of these structures exist. Namely, our "internalizing/detached" subgroup may also correspond to the detachment spectra outlined in the HiTOP model whilst our "externalizing/antisocial group" as noted above may be considered to encompass the externalizing and thought disordered spectra (Kotov et al., 2017). Further, although our group sizes were broadly in line with expectations, a consequence of our data-driven clustering method was that the classes derived exhibited unbalanced group sizes, and thus displayed unequal variance across SP measures. Although this precluded proceeding with our planned group analyses (ANOVAs), the analysis approach we adopted (WTPS) given the heteroscedacity and unequal group sizes offers stricter control over type 1 error and greater power in comparison to the traditional F statistic ANOVA (Helwig, 2019; Pauly et al., 2015). Further, although we utilized a high number of permutations in our LCA, cross-validation of our class structure in independent or larger samples would lend further validity to the stability of our findings. Finally, we acknowledge that performance on certain SP tasks may have been influenced by other neurodevelopmental abilities that were not directly assessed in this study. In particular, some of the SP tasks selected (e.g., MASC) notably rely on receptive language abilities which have been established as important for real-life social functioning (e.g., Conti-Ramsden et al., 2013). In parsimony with the RDoC approach, future studies could extend the present findings by exploring whether expressive/receptive language abilities are associated with specific trait and SP profiles.

Notwithstanding these limitations, our findings are noteworthy in several ways and provide important implications for future research and the ongoing development of the AMPD. Firstly, our results provide support for a dimensional-categorical (or 'hybrid') model of psychopathology, in line with the conceptualization proposed in the AMPD model (American Psychiatric Association, 2013). Utilizing an influential dimensional model, the AMPD, we found distinct and meaningful classes that were distributed along a severity continuum (dimensional component), with a clear dissociation between two 'medium' WILEY

classes (categorical component; Gamache et al., 2021). Interestingly, the characteristics of our four classes were similar to those found in a recent study in a clinical sample of patients with borderline pathology (Gamache et al., 2021). The authors of this study utilized Criterion A and the Criterion B facets assigned to borderline personality disorder to derive four distinct profiles: a less severe profile, a high psychopathology profile, and two intermediate profiles, one with higher externalizing features, and one with higher internalizing features. Remarkably, the 'internalizing' profile found in the Gamache et al. (2021) study also exhibited striking similarities to the clinical symptoms and SP profile of our 'internalizing' group: they were characterized by higher levels of depressivity and identity ('self')-related dysfunction (Gamache et al., 2021). As we did not include a measure of Criterion A in our study, we cannot comment directly on the relationship between Criterion A and the RDoC 'Systems for Social Processes'. However, the conceptual overlap and similarities between the internalizing-related Criterion A 'identity' issues in the study by Gamache et al. (2021) and our internalizing-related 'self' SP deficits propose an interesting avenue for future exploration: whether Criterion A and the RDoC 'Systems for Social Processes' are closely related, or represent similar constructs viewed through different lenses or paradigms. Such research would contribute to the ongoing debate in the AMPD literature regarding the conceptualization of Criterion A (e.g., Morey, 2019; Sleep et al., 2019), which has emerged based on evidence that Criterion A and B exhibit high levels of redundancy (Widiger et al., 2019), despite being intended to represent distinct components of personality (American Psychiatric Association, 2013). Tentatively, our findings support the assertion by Morey et al. (2020): that self and interpersonal pathology, as broadly captured in both Criterion A of the AMPD and the RDoC 'Systems for Social Processes', and maladaptive personality traits (i.e., Criterion B) should be conceptualized as interrelated rather than separate criteria. Future research exploring whether Criterion A self/interpersonal deficits fall within specific trait domains or spectra (i.e., self on internalizing/ detached traits/spectra, interpersonal on externalizing traits/spectra) would further build on the findings of our study and support the ongoing refinement of dimensional models of psychopathology.

Further, the two 'medium' groups identified in our LCA displayed clear dysfunction in SP and endorsed higher levels of clinical symptoms in comparison to the "low psychopathology" group, which supports the importance of identifying 'subthreshold' groups that may display clinically relevant difficulties (Kozak & Cuthbert, 2016). It is important to emphasize that these subthreshold groups would traditionally be 'missed' in the categorical approach

to research; a factor likely contributing to the significant heterogeneity present in the SP literature. Further, the mean trait scores for the high psychopathology group and the high trait scores for the 'medium' groups (i.e., antagonism for externalizing, detachment for internalizing) were comparable to psychiatric populations, suggesting that these may represent clinically relevant levels of maladaptive traits (Quilty et al., 2013). Future research incorporating measures of social functioning and clinical outcomes would further contribute to our understanding of the clinical relevance of latent trait subgroups. Secondly, it is important to note that we found significant differences between our subgroups in measures that have historically been neglected in the SP literature (i.e., reception of nonfacial communication, self-concept, sense of commitment). This highlights the clear need to utilize established frameworks such as the 'Systems for Social Processes' domain to allow accurate and comprehensive characterization of SP. Finally, although preliminary, our findings emphasize the importance of utilizing a transdiagnostic approach to SP research. Research seeking to replicate these findings in larger or clinical samples is important, given its potential to ameliorate problems of heterogeneity within the SP literature and contribute to the refinement of dimensional systems of psychiatry.

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CONFLICTS OF INTEREST

The authors have declared no conflicts of interest for this article.

AUTHOR CONTRIBUTIONS

Lauren Hanegraaf: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualisation, Project Administration. Antonio Verdejo-Garcia: Conceptualization, Writing -Review & Editing, Supervision, Funding acquisition. Jakob Hohwy: Conceptualization, Writing - Review & Editing, Supervision, Funding acquisition.

ETHICS APPROVAL STATEMENT

All data were collected in a manner consistent with ethical standards for the treatment of human subjects.

ORCID

Lauren Hanegraaf https://orcid. org/0000-0003-3243-2708 Jakob Hohwy https://orcid.org/0000-0003-3906-3060 Antonio Verdejo-Garcia https://orcid. org/0000-0001-8874-9339

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