128 (2025) 202712

Contents lists available at ScienceDirect

Research in Autism

journal homepage: www.elsevier.com/locate/rasd

Predicting autistic traits, anxiety and depression symptoms using camouflaging autistic traits questionnaire (CAT-Q-ES): A machine learning study

Sabela Conde-Pumpido Zubizarreta [a,1], María Tubío-Fungueiriño [a,b,c,1], Marta Pozo-Rodríguez [a], Angel Carracedo [a,c,d,e], Eva Cernadas [f], Manuel Fernández-Delgado [f,2], Montse Fernández-Prieto [a,b,c,d,*,2]

[a] Genomics and Bioinformatics Group, Center for Research in Molecular Medicine and Chronic Diseases (CiMUS), Universidade de Santiago de Compostela (USC), Santiago de Compostela, Spain
[b] Fundación Pública Galega Instituto de Investigación Sanitaria de Santiago de Compostela (FIDIS), Santiago de Compostela, Spain
[c] Genetics Group, Instituto de Investigación Sanitaria de Santiago (IDIS), Santiago de Compostela, Spain
[d] Centro de Investigación Biomédica en Red de Enfermedades Raras, Instituto de Salud Carlos III, Madrid, Spain
[e] Fundación Pública Galega de Medicina Xenómica, Servicio Galego de Saúde (SERGAS), Santiago de Compostela, Spain
[f] Centro Singular de Investigación en Tecnoloxías Intelixentes (CiTIUS) da Universidade de Santiago de Compostela, Santiago de Compostela, Spain

ARTICLE INFO

Keywords:
ASD
Autism
CAT-Q-ES
Camouflaging
Supervised machine learning
Mental health
Gender

ABSTRACT

Research has linked camouflaging with compensating and hiding autistic traits during social interactions. Furthermore, these strategies have been linked to increased anxiety and depression symptoms and to greater reliance on camouflaging behaviors among individuals with more autistic traits, even in non-autistic populations. This study evaluated the viability of a machine learning algorithm to predict autistic traits and symptoms of depression and anxiety using camouflaging behaviors. The sample included 601 participants: 102 autistic adults (72 women, 18 men, and 12 non-binary individuals) and 499 non-autistic adults (399 women, 92 men, and eight non-binary individuals). The study predicted autistic traits measured with the Broader Autism Phenotype Questionnaire (BAPQ) subscales - Aloofness, Pragmatics, and Rigidity - as well as the total score of depressive (Patient Health Questionnaire - PHQ-9) and anxious symptoms (General Anxiety Disorder - GAD-7) using the individual items from the Camouflaging Autistic Traits Questionnaire Spanish version (CAT-Q-ES) as predictors. We developed fifty supervised learning models, including support vector machines, neural networks, linear regressors, decision trees, random forests, and Gaussian processes, among others. Correlation coefficients between true and predicted scores were strong for Aloofness (R=.85), Pragmatics (R=.82), and Rigidity (R=.74), being only moderate for Depression (R=.60) and Anxiety (R=.54). Autism diagnosis or gender identity did not improve the prediction's accuracy. These results show the viability of machine learning algorithms to predict autistic traits (Aloofness, Pragmatics and Rigidity) and anxiety-depression symptoms, using the CAT-Q-ES. This suggests potential for developing a tool

* Correspondence to: CiMUS, Avda. de Barcelona, s/n, 15702 Edificio P2, D3, Santiago de Compostela, A Coruña, Spain
E-mail address: montse.fernandez.prieto@usc.es (M. Fernández-Prieto).

[1] These authors share first authorship.

[2] These authors share last authorship.

https://doi.org/10.1016/j.reia.2025.202712
Received 5 May 2025; Received in revised form 8 September 2025; Accepted 15 September 2025
Available online 20 September 2025

that may improve autistic traits and emotional problems screening in individuals whose diagnosis is unclear or not yet established, regardless of gender identity.

Introduction

Camouflaging refers to the verbal and non-verbal strategies used by neurodivergent/autistic individuals to model neurotypical behavior, thereby minimizing their differences' visibility and facilitating social relationships and adaptation (Ai et al., 2022). Indeed, camouflaging behaviors are social coping mechanisms broadly studied in autism (i.e., camouflaging autistic traits, autistic camouflaging, masking, or social camouflaging).

Several studies have investigated camouflaging behaviors across neurodivergence, e.g., Attention-Deficit/Hyperactivity Disorder (ADHD) (van der Putten et al. 2024; Wicherkiewicz, Gambin, 2024) and developmental language disorder (Hobson & Lee, 2023). Consistent with this, camouflaging was found to correlate with autistic traits in both autistic and non-autistic individuals (Dell'Osso et al., 2022; Hull et al., 2019; Lundin Remnélius & Bölte, 2023). These findings suggest that camouflaging behaviors are distributed dimensionally across the general population rather than exclusively to autism (Ai et al., 2023; Hull et al., 2019; Lundin Remnélius & Bölte, 2023).

Although camouflaging has an adaptive purpose, it negatively impacts the mental health of autistic individuals, contributing to burnout, depression, and anxiety (Cook et al., 2021). These strategies were also associated with delayed autism diagnosis in women (Milner, Colvert, et al., 2023; Perry et al., 2022), and correlational studies in autistic individuals with lower support needs have found that those with more pronounced autistic characteristics are more likely to adopt camouflaging strategies (Cook et al., 2021), and this relationship may be mediated by stigma perception (Perry et al., 2022). Additionally, higher camouflaging has been related to reduced quality of life (Lundin Remnélius et al., 2024; Milner et al., 2023), and it has been identified as a risk factor for suicidal ideation and behaviors even in non-autistic adults (Cassidy et al., 2023).

Some studies showed that using camouflaging strategies had more negative effects on autistic women (Milner et al., 2023; Tubío-Fungueiriño et al., 2021) and non-autistic women (Somerville et al., 2024) compared to men. Some research hypothesized that non-binary/gender-diverse individuals would display more autistic trait camouflaging behaviors, as they might face greater stigma and minority stress than cis-gender individuals (Botha & Frost, 2020; Chew et al., 2020). However, there is still a lack of methodologically appropriate studies capable of capturing gender differences or the complex association between gender identity and camouflaging (Ai et al., 2023; Cruz et al., 2024; Perry et al., 2022). This was particularly relevant as research highlighted the high prevalence of autistic people who reported a transgender identity, as well as a notable prevalence of transgender people with an autism diagnosis (Bouzy et al., 2023). Qualitative reports also suggested that non-binary or trans autistic individuals may mask both autistic and gendered traits (Hake, 2024; Peachey & Crane, 2024), indicating greater pressure to fit in and an extra motivation to camouflage.

Despite growing interest in camouflaging and evidence of increased burden for women and non-binary people (Beck et al., 2020; Somerville et al., 2024; White et al., 2024), existing research relied on traditional statistical methods to study its predictors and outcomes. Yet, the findings about the relationship between camouflaging, autistic traits and mental health outcomes in autistic and non-autistic adults remain inconsistent. Hull et al. (2021) found that camouflaging was associated with anxiety and depression in autistic adults, but this was partly explained by autistic traits and age. However, Moore et al. (2024) found that the relationship between autistic traits and mental well-being was fully mediated by camouflaging. Considering non-autistic adults, Lorenz and Hull (2024) reported that camouflaging, linked to autistic traits and anxiety, was correlated with lower depression risk.

Given the complex relationship between camouflaging, autistic traits and mental health outcomes, machine learning techniques might offer a promising approach by identifying patterns that may not be evident through conventional statistical methods (Agne et al., 2022; Fernández-Delgado et al., 2024; Segalàs et al., 2024; Tubío-Fungueiriño et al., 2024).

Machine learning techniques were used to detect patterns in data, make inferences, and apply these learned patterns to predict future data or support decision-making tasks (Alpaydın, 2020; Murphy, 2012). Abdelhamid et al. (2023) applied machine learning models to Quantitative Checklist for Autism in Toddlers (Q-CHAT-10; Allison et al., 2012) data from toddlers aged 12–36 months to identify which autistic traits most strongly contribute to early autism screening. By selecting the most informative items, the classifiers demonstrated strong performance, with reported accuracy, sensitivity, and specificity metrics generally ranging between 85 % and 95 %. Rajab et al. (2021) developed machine learning models also using Q-CHAT-10 to classify toddlers with or without autistic traits, in which the best classifier obtained an accuracy of 98.34 %, a sensitivity of 98.70 %, and a specificity of 97.77 %. Additionally, recent research has applied multimodal machine learning to improve autism screening, such as video-based approaches combining multi-camera data with multiple extracted behavioral metrics (Zhu et al., 2023) and models integrating facial image analysis with scores from gold-standard diagnostic tools (Sellamuthu and Rose, 2024). Similarly, Fernández-Delgado et al. (2024) applied machine learning to predict ADHD co-occurrence in autistic children and adolescents based on sensory processing patterns, aiding early identification of neurodevelopmental conditions. Similarly, Tubío-Fungueiriño et al. (2024) developed an algorithm to predict pharmacological responses in patients with Obsessive-Compulsive Disorder (OCD) and optimize treatment selection. Following this approach, autistic individuals—especially women—often experienced significant delays in receiving a diagnosis. Delays in diagnosis were detrimental for mental health and often led to more camouflaging strategies (McQuaid et al., 2022). Thus, camouflaging behaviors have been related to autistic traits, diagnosis delays, and mental health issues. Therefore, the development of machine learning algorithms may facilitate a timelier identification of autistic traits and symptoms of anxiety and depression; allowing mental health professionals to provide an appropriate diagnosis and personalized interventions.

Based on prior literature, we hypothesize: (1) information provided by self-reported camouflaging measured with Camouflaging Autistic Traits Questionnaire (CAT-Q-ES, Conde-Pumpido Zubizarreta et al., 2025) can predict scores of autistic traits and anxiety and depression symptoms, and (2) including diagnostic status and gender as input variables will improve the predictive accuracy of the models.

The current study aims to examine whether machine learning models based on the CAT-Q-ES scores can predict autistic traits, anxiety, and depression symptoms in an autistic and non-autistic adult sample. Also, with our methodological approach, we aimed to identify if gender and diagnosis status may introduce more information that improves the prediction accuracy.

Method

Participants

The sample comprised 601 adults (471 women, 110 men, and 20 non-binary individuals; mean age=33.7; standard deviation [SD]=11.0). Among them, 102 had a formal autism diagnosis from specialized clinicians (72 women, 18 men, and 12 non-binary individuals; mean age = 36.0; SD = 10.6), with a mean age at diagnosis of 32.0 years (SD = 12.3). Non-autistic participants included 399 women, 92 men, and eight non-binary participants (mean age=33.3; SD=11.0). Autistic participants were, on average, 2.7 years older than non-autistic participants ($t(599) = 2.24$, $p = .025$, $d = 0.24$ [95 % CI.03–.46]). Significant differences in gender distribution were observed between groups. The autistic group had a lower proportion of women ($Z = -2.10$, $p = .036$ [95 % CI −.19-(-.06)]) but a higher proportion of non-binary participants compared to non-autistic participants ($Z = 5.21$, $p < .001$ [95 % CI.05–.18]). Information on comorbidities and psychiatric disorders in autistic and non-autistic participants is presented in Table 1.

Procedure

This study was part of a broader project that aims to validate the CAT-Q for the Spanish population. Data was collected and managed using REDCap (Research Electronic Data Capture) tools hosted at Fundación Pública Galega de Medicina Xenómica (Harris et al., 2009, 2019). REDCap is a secure, web-based software platform designed to support data capture for research studies, providing 1) an intuitive interface for validated data capture; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for data integration and interoperability with external sources. The research team created a survey on REDCap and disseminated it through autism associations, institutions, federations, clinical units, autism-related research networks, and social media.

The primary section of the survey provided information about the study and included a statement of consent to participate. Participants were asked about their clinically based diagnosis of autism and the kind of professional who made the diagnosis. Those who reported being self-diagnosed ($n = 12$) were excluded. Additionally, participants with autism were asked about the clinically based diagnosis of other comorbidities associated with autism, such as other neurodevelopmental disorders, bipolar disorder, and anxiety/

Table 1
Level of education and self-reported clinical conditions for the autistic and non-autistic groups.

	Autistic		**Non-autistic**		
	N	%	N	%	T-test / Wald test
Age (M / SD)	36.0	10.6	33.3	11.0	p = .025
Gender					
Women	72	70.6	399	80.0	p = .036
Men	18	17.6	92	18.4	p = .851
Non-binary	12	11.8	8	1.6	p < .001
Level of Education					
No studies	-	-	1	.2	
Elementary Education	-	-	2	.4	
Secondary Education	10	9.8	41	8.2	
Vocational Training	15	14.7	36	7.2	
Degree	63	61.8	324	64.9	
Higher Vocational Training	10	9.8	28	5.6	
PhD	4	3.9	67	13.4	
Self-reported clinical conditions					
High Abilities	33	32.4	28	5.6	
Attention Deficit/Hyperactivity Disorder	23	22.5	22	4.4	
Developmental Coordination Disorder	1	1.0	1	.2	
Specific Learning Disorder	7	6.9	7	1.4	
Epilepsy	0	-	4	.8	
Bipolar Disorder	2	2.0	0	-	
Eating Disorder	14	13.7	27	5.4	
Anxiety	50	49.0	94	18.8	
Depression	31	30.4	59	11.8	
Sleeping Disorder	19	18.6	22	4.4	
Other	15	14.7	13	2.6	

depressive disorders. Those without autism were asked about any other formal neurodevelopmental or psychiatric diagnoses. All clinically based diagnoses reported in this study were self-reported by participants.

The survey collected both for assigned at birth sex and for self-reported gender, but this work focused on self-reported gender, as it better reflects participants' identities. Only individuals who identified as women, men, or non-binary individuals were included. Participants who did not report their gender (n = 13; four selected 'prefer not to answer', six 'not sure' and three individuals selected 'other') were excluded. All participants were Spanish nationals or residents and provided informed consent before completing the CAT-Q-ES. There were 14 participants who had one missing item and one participant that had two missing items in the Patient Health Questionnaire 9 (PHQ-9; Kroenke et al., 2001), corresponding to.30 % missing data. Considering the small amount of missing data and the fact that the PHQ-9 is a unidimensional measure of depressive symptoms, we performed a person-level imputation method, and missing values were imputed to the mean. This study was performed in line with the principles of the Declaration of Helsinki. The Ethics Committee of the University of Santiago de Compostela (Code: USC 26/2023) reviewed and approved of the present study. The anonymity of the participants was always preserved during data collection.

Materials

Camouflaging

The items from the Camouflaging Autistic Traits Questionnaire Spanish Version (CAT-Q-ES, Conde-Pumpido Zubizarreta et al., 2025) were used as input variables for developing the machine learning models. The CAT-Q-ES is a self-report measure that assesses camouflaging behaviors. This questionnaire consists of twenty-five items, rated on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree). Three subscales – compensation, with items describing strategies such as copying others' behaviors or preparing scripts to navigate social situations; masking which comprises items about controlling and/or adjusting face and body expression to fit in; and assimilation, which refers to performance, effortful engagement, and pretending to be 'normal' in social situations (Hull et al., 2019). The validation study reported an internal consistency (McDonald's omega [ω]) of.95 for the full scale in autistic and non-autistic participants (Conde-Pumpido Zubizarreta et al., 2025). Higher scores indicate higher levels of camouflaging. We used the three CAT-Q-ES subscales and the total score to test for group differences.

Autistic traits

Autistic traits were measured using the Broader Autism Phenotype Questionnaire (BAPQ; Hurley et al., 2007), a 36-item self-report designed to assess dimensional autistic traits in the relatives of autistic individuals. The questionnaire consists of three subscales: Aloof Personality, Rigid Personality, and Pragmatic Language. Participants rated the frequency with which they experienced these traits on a scale from 1 (Very rarely) to 6 (Very often). The Spanish validation (Godoy-Giménez et al., 2018) reported good psychometric properties with limitations in the Pragmatic Language subscale. In the validation study, Cronbach's a coefficient was.94 for the Aloof Personality,.85 for the Pragmatic Language, and.91 for the Rigid Personality subscale and.95 across the full scale (Hurley et al., 2007). The BAPQ is widely used as a measure of quantitative autistic traits in both autistic and non-autistic populations (Hull et al., 2021; Nishiyama & Kanne, 2014a; Nishiyama et al., 2014b). In the present study, we aimed to predict scores on the BAPQ subscales: Aloof Personality (Aloofness), Pragmatic Language (Pragmatics), and Rigid Personality (Rigidity). Higher scores indicate a stronger expression of autistic traits.

Depression symptomatology

The Patient Health Questionnaire 9 (PHQ-9; Kroenke et al., 2001), Spanish version (Diez-Quevedo et al., 2001) was used to assess depressive symptoms. The PHQ-9 is a widely used and clinically validated screening tool that assesses the Major Depressive Disorder (MDD) severity in the last two weeks based on the Diagnostic and Statistical Manual of Mental Disorders 4th edition (DSM-IV, APA, 1994) criteria. It was used in other camouflaging autistic traits studies (Hull et al., 2021) and shows invariance between autistic and non-autistic populations, except for one item (Robeson et al., 2024). Kroenke et al. (2001) reported an excellent internal consistency (ω=.89). This supports its use in both autistic and non-autistic samples for assessing depression symptomatology. It consists of nine items, answered on a Likert scale from 0 (Not at all) to 3 (Almost every day). The items cover sleep, energy, appetite, and other symptoms of depression. The total score was calculated by adding up all the items and indicates how often a person experiences these feelings, with higher scores reflecting more severe symptoms. In this study, we use the total score of this scale as an output measure to predict depressive symptom screening scores.

Anxiety symptomatology

We used the Generalized Anxiety Disorder 7 (GAD-7; Spitzer et al., 2006), Spanish version (García-Campayo et al., 2010) to assess anxiety. GAD-7 is a widely used screening tool that measures the severity of Generalized Anxiety Disorder (GAD) in the last two weeks following DSM-4 criteria. This self-report has also shown measure invariance between autistic and non-autistic populations. It consists of seven items that measure the frequency of various anxiety symptoms over the past two weeks (e.g., 'Worrying too much about different things'). Respondents answered each item on a Likert scale from 0 (Not at all) to 3 (Nearly every day). The total GAD-7 score was obtained by summing up all the items, and this value was used in the analysis. Higher scores indicate greater severity of anxiety symptomatology. The GAD-7 demonstrates good sensitivity and specificity and has high internal consistency. In the Spanish validation study (García-Campayo et al., 2010), the GAD-7 showed an excellent internal consistency (ω=.94).

Data analysis

Descriptive analyses

We used IBM Statistical Package for Social Sciences (SPSS), version 29 for Windows (IBM Inc.) to assess group (autistic and non-autistic participants) and gender differences in the CAT-Q-ES total score and subscales (Compensation, Masking, and Assimilation); BAPQ subscales (Aloofness, Pragmatics, and Rigidity) and the GAD-7 and PHQ-9 total scores. Assumption checks indicated that the data did not meet normality criteria according to the Kolmogorov-Smirnov test—in the case of larger samples, as the women's group, and variance homogeneity was also violated for some variables according to Levene's test. However, the Shapiro-Wilk test did not indicate significant deviations from normality in the non-binary group, likely due to the small sample size. Given these violations and the unequal sample sizes across gender groups, the Mann-Whitney *U* test and non-parametric Kruskal-Wallis tests with Bonferroni corrections were used to test group and gender differences in the full sample. Internal consistency was tested for CAT-Q-ES, GAD-7 and PHQ-9 total score and for BAPQ total scores and subscales using McDonald's omega (ω) to ensure the reliability of our measures in the present sample.

Machine learning analyses

The model inputs were camouflaging behaviors, gender (woman, man, or non-binary), and autism diagnosis (autistic or non-autistic); while the model outputs were autistic traits and anxiety and depression symptoms. A collection of supervised machine learning models was used to predict BAPQ, PHQ-9, and GAD-7 scores from CAT-Q-ES items. Specifically, the BAPQ scores were Pragmatics, Aloofness, and Rigidity. Additionally, PHQ-9 and GAD-7 scores were briefly labeled as 'Depression' and 'Anxiety', respectively. We chose to use the raw scores from the BAPQ subscales instead of the averaged scores to maintain the variability in the data. Fig. 1 shows the box plots of these five scores. The vertical blue segments show the upper and lower limits for each score: 0–21 for Anxiety, 0–27 for Depression, 12–72 for Aloofness and Rigidity, and 14–71 for Pragmatics. To test the impact of autism diagnosis and gender on the prediction, we repeated the experiments using: (1) only CAT-Q-ES items; (2) CAT-Q-ES items and gender (without autism diagnosis); (3) CAT-Q-ES items and autism diagnosis (without gender); and (4) all CAT-Q-ES items, gender, and autism diagnosis. Additionally, we tested items from different CAT-Q-ES subscales to determine whether using Compensation (items 1, 4, 5, 8, 11, 14, 17, 20, and 23), Masking (items 2, 6, 9, 12, 15, 18, 21, and 24), or Assimilation (items 3, 7, 10, 16, 19, 22, and 25) improved the prediction accuracy for any of the outputs. Given that using CAT-Q-ES subscales did not improve prediction accuracy, these results were not reported in this paper.

Since the outputs in Fig. 1 were continuous, the prediction of their values was a regression problem. Appendix 1 in the Supplementary material list the 50 machine learning regression models used in our experiments, implemented in the Python, R, Matlab and Octave programming languages (Fernández-Delgado et al., 2019), alongside with the package used by each model and hyperparameter tuning details. The code, alongside with a small sample data, are publicly available from the OSF Science Foundation (https://osf.io/t5v62).

To evaluate the reliability of the machine learning models for the prediction of BAPQ, depression (PHQ-9), and anxiety (GAD-7) scores, the experimental methodology that we used was the well-known K-fold two-layer cross-validation, in our case with K= 4. This

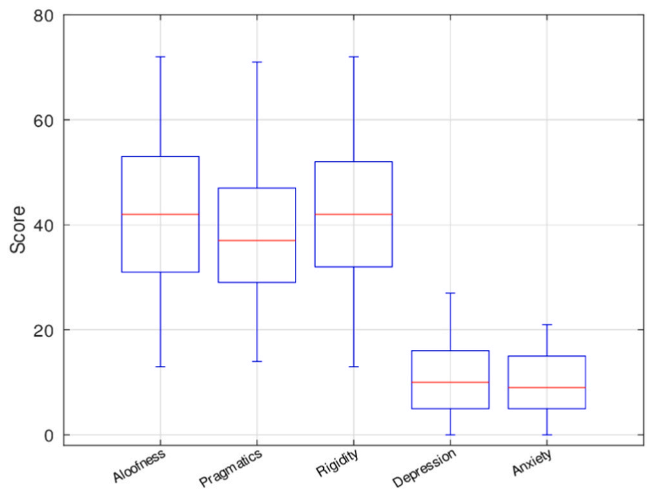

Fig. 1. Box Plots and Lower-Upper Limits for the Five Scores Predicted.

procedure performed four trials. The available dataset (601 participants) was divided into four partitions. To ensure the representativeness of the dataset, participants across the entire score range were included in each partition. Each participant was included in exactly one partition, so the four partitions were disjointed. In each trial, two partitions were devoted to training, one for validation and the remaining partition for test. The training, validation, and test partitions were different among trials. Each partition was used in some trials for training, in others for validation, and in others for testing.

Each regressor (such as linear regression) without tunable hyper-parameters was trained on the training and validation partitions jointly. Then, it was used to predict the score for the participants on the test partition, evaluating a performance metric, specifically the mean absolute error (MAE, see below). This procedure was repeated for each trial, and the test MAE of each trial was averaged over the four trials, giving the average test MAE.

When the regressor has tunable hyper-parameters, such as regularized linear regression or support vector regression, it was trained for each trial on the training partitions using several combinations of the hyper-parameter values. Then, the regressor, trained using each combination, predicted the score for participants on the validation partition, and MAE was evaluated. The combination with the best validation MAE was used to train the regressor on the training and validation partitions jointly. Then, the trained regressor was used to predict the score on the test set, and the test MAE was calculated. This procedure was repeated in the four trials, and each trial used its corresponding collection of training, validation, and test partitions. The average test MAE was the average of the test MAE values over the four trials.

The average test MAE and other performance metrics averaged over the four trials were reported for the five scores predicted: Aloofness, Pragmatics, Rigidity, Depression, and Anxiety. These metrics, described in Appendix 2 of the Supplementary Material, were Pearson's correlation coefficient (R), the MAE, mean absolute percentage error of the score range (MAPE), and root mean square error (RMSE). According to Colton (1974), the value of a correlation R below.25 means a null correlation between true and predicted values; values between.25 and.5 indicate a weak correlation; from.5 to.75 can be classified as moderate; and correlations above.75 are deemed strong. Diagrams of true and predicted scores are also generated.

Results

The results indicated a significant difference between autistic and non-autistic participants in the CAT-Q-ES total score (Mann-Whitney U=7820.00, $p < .001$), Compensation (U=7265.50, $p < .001$), Masking (U=14644.50, $p < .001$), Assimilation (U=9556.50, $p < .001$), Aloofness (U=9725.50, $p < .001$), Pragmatics (U=7526.00, $p < .001$), Rigidity (U=9151.50, $p < .001$), Anxiety (U=13507.50, $p < .001$) and Depression (U=12583.00, $p < .001$). Higher mean ranks in the autistic groups indicated these participants outscored non-autistic participants. Non-binary people scored significantly higher than women and men on all outcomes except Depression and Anxiety, where they overscored only men (see Table 2). There were no differences found between women and men in the studied variables. The internal consistency in the present sample was CAT-Q-ES (ω =.96), GAD-7 (ω =.92), PHQ-9 (ω =.91) total scores, and for the BAPQ subscales: Aloofness (ω =.94), Pragmatics (ω =.87), Rigid Personality (ω =.92), and the full scale (ω =.96).

Table 2
Mean (M) and Standard Deviation (SD) values for the full sample and gender differences within groups in all variables.

	Total	Women	Men	Non-binary people	Kruskal-Wallis	
	Range M(SD)	Range M(SD)	Range M(SD)	Range M(SD)	H(df) p-value	
CAT-Q-ES Total Score	30–162	30–162	45–157	82–161	15.2(2)	NB>W**
	100.4 (32.2)	99.5 (32.9)	99.4 (28.6)	128 (22.6)	< .001	NB>M*
Comp	9–63	9–63	9–60	24–61	22.4(2)	NB>W**
	31.3 (14.3)	30.5 (14.4)	31.9 (13.1)	46.5 (10.8)	< .001	NB>M**
Masking	8–56	8–56	8–50	22–50	8.8(2)	NB>W*
	35.5 (9.2)	35.5 (9.4)	34.4 (8.2)	40.2 (8.8)	.012	NB>M*
Assim	8–56	8–56	10–55	29–52	7.7(2)	NB>W*
	33.7 (12.5)	33.5 (12.8)	33.1 (11.5)	41.4 (6.9)	.021	NB>M*
Aloofness	13–72	13–72	17–71	35–66	9.9(2)	NB>W*
	42 (13.8)	41.5 (14.1)	42.7 (12.7)	50.8 (8.6)	.007	NB>M*
Pragmatics	14–71	14–71	18–64	33–62	23.4(2)	NB>W**
	37.8 (11.9)	37.1 (11.9)	39.0 (11.0)	49.6 (7.9)	< .001	NB>M**
Rigidity	13–72	13–72	13–67	36–67	13.9(2)	NB>W*
	42.2 (13.4)	41.4 (13.9)	43.8 (11.3)	51.1 (8.4)	< .001	NB>M*
PHQ−9	0–27	0–27	0–24	2–25	7.2(2)	NB>M*
	10.8 (6.9)	10.8 (7.0)	9.8 (6.2)	14.8 (7.5)	.027	
GAD−7	0–21	0–21	0–21	4–21	11.1(2)	NB>M*
	10 (5.8)	10.2 (5.8)	8.7 (5.3)	13.2 (5.8)	.004	

Note. SD=Standard Deviation; CAT-Q-ES=Camouflaging Autistic Traits Questionnaire Spanish Version; BAPQ=Broad Autism Phenotype Questionnaire; PHQ-9 =Patient Health Questionnaire; GAD-7 =Generalized Anxiety Disorder 7.
*$p < .05$
**$p < .001$

Predicting autistic traits, depression, and anxiety with CAT-Q-ES items and gender

Rows 4–9 in Table 3 reported the correlation R, and its corresponding MAE, MAPE (in %), and RMSE achieved by the best regressor for each score, using CAT-Q-ES as input data. The reliability of the prediction of Aloofness (R=.85) and Pragmatics (R=.82) was considered strong according to the Colton criteria. Regarding Rigidity (R=.74), Anxiety (R=.54), and Depression (R=.60), the correlations were only considered as moderate.

The reliability of prediction was variable across all regressors, with the prediction for autistic traits being more reliable than for anxiety and depression scores. The MAE values for Aloofness, Pragmatics, and Rigidity ranged between 4.5 and 7, on a scale from 12 to 72, which indicated low absolute error. The MAPE was below 10 % for Aloofness and Pragmatics, and it was slightly higher for Rigidity (11.6 %).

Although MAE (4.55 and 3.97) for Depression and Anxiety was lower than for autistic traits scores, this was due to their smaller ranges (27 and 21 for Depression and Anxiety, respectively, being 57–60 for autistic traits scores). Relating to Depression, the MAE was 4.55 over a range of 27, resulting in a MAPE of 16.9 %, which was well above the 10 % threshold. About Anxiety, the predictive reliability was intermediate, with an MAE of 4.00 over a range of 21, giving a MAPE of 19.1 %, much higher than for the prediction of autistic traits.

Considering the lowest MAE and MAPE values of each machine learning model, the most reliable predictions were achieved by SGD (stochastic gradient descent) in Aloofness, SVR (support vector regression) in Pragmatics, regularized Ridge regression in Rigidity, KNN (k-nearest neighbors) in Depression and BstTree (boosting ensemble of regression trees) in Anxiety. Regarding the programming language, the best regressors were implemented in Python for Aloofness and Depression, in Matlab for Pragmatics and Rigidity, and in R for Anxiety.

Fig. 2A showed the prediction performance of the best regressor (SGD) for the Aloofness score. The left panel plotted the predicted score (vertical axis) against the true score (horizontal axis) for each participant (blue dots), alongside with a dashed trend line (Fig. 2A left). The distribution showed that, overall, lower true scores corresponded to lower predicted values and higher true scores to higher predicted values. Besides, the trend line closely followed the red diagonal line, which represents perfect agreement between predicted and true scores. The panel displayed predicted values closely matched the true scores, especially in the mid-range but also at both extremes, demonstrating a reliable fit. Since machine learning methods are intrinsically approximated, we cannot expect a perfect prediction extremely near to the true score (e.g., within five units around it).

The right panel of Fig. 2A (right) showed the percentage of participants whose scores were predicted within a given tolerance. Tolerance is defined as the maximum allowable absolute difference between predicted and true scores, expressed as a percentage of the Aloofness score range (60). For example, a 5 % tolerance corresponds to 3 units (60 × 0.05). In the plot, the tolerance varied from 0 % to 50 %. The blue line indicated the performance of the SGD regressor, while the red line corresponded to a "default" regressor that always predicts (for any value of the input data) the mean value of the Aloofness score, representing a low-reliability prediction. A closer proximity of the blue line to the left vertical axis of the graph, or a larger space between blue and red lines, indicated a better predictive accuracy. In Fig. 2A (right), the blue line in the right plot was fairly separated from the red line, indicating a highly reliable prediction. Additionally, the model predicted 36.3 % of cases within 5 % around the true value, defined as P5 (i.e., the model predicts a score within ±5 % of the true value for 36.3.% of cases). When the tolerance increased to 10 %, the percentage of cases would increase above 60 %. For example, since the Aloofness score ranges from 12 to 72 points, if a person's true score is 20, the algorithm will predict

Table 3
Best correlation (R), MAE, MAPE (In %), RMSE, Regressor and language using CAT-Q-ES as inputs (Rows 4–9); R and MAE Using CAT-Q-ES and Gender (Rows 11–12); R and MAE using CAT-Q-ES and Autism diagnosis (Rows 14–15); R and MAE using CAT-Q-ES, Gender and Autism Diagnosis (Rows 17–18).

Test	BAPQ			PHQ – 9	GAD – 7
Score	Aloofness	Pragmatics	Rigidity	Depression	Anxiety
CAT-Q-ES					
R	.85	.82	.75	.58	.54
MAE	5.55	5.36	6.94	4.55	4.00
MAPE (%)	9.2	8.9	11.6	16.9	19.1
RMSE	7.22	6.90	8.92	5.71	4.91
Regressor	SGD	SVR	Ridge	KNN	BstTree
Language	Python	Matlab	Matlab	Python	R
CAT-Q-ES and gender					
R	.85	.82	.75	.60	.53
MAE	5.55	5.32	6.92	4.52	3.98
CAT-Q-ES and autism diagnosis					
R	.85	.83	.75	.60	.54
MAE	5.53	5.29	6.91	4.46	3.98
CAT-Q-ES, gender and autism diagnosis					
R	.85	.83	.75	.61	.54
MAE	5.54	5.31	6.84	4.48	3.97

Note. R=Pearson's correlation coefficient, MAE=mean absolute error, MAPE=mean absolute percentage error of the score range, RMSE=root mean square error, SGD=stochastic gradient descent, SVR=support vector regression, KNN=k-nearest neighbors, BstTree= boosting ensembles.

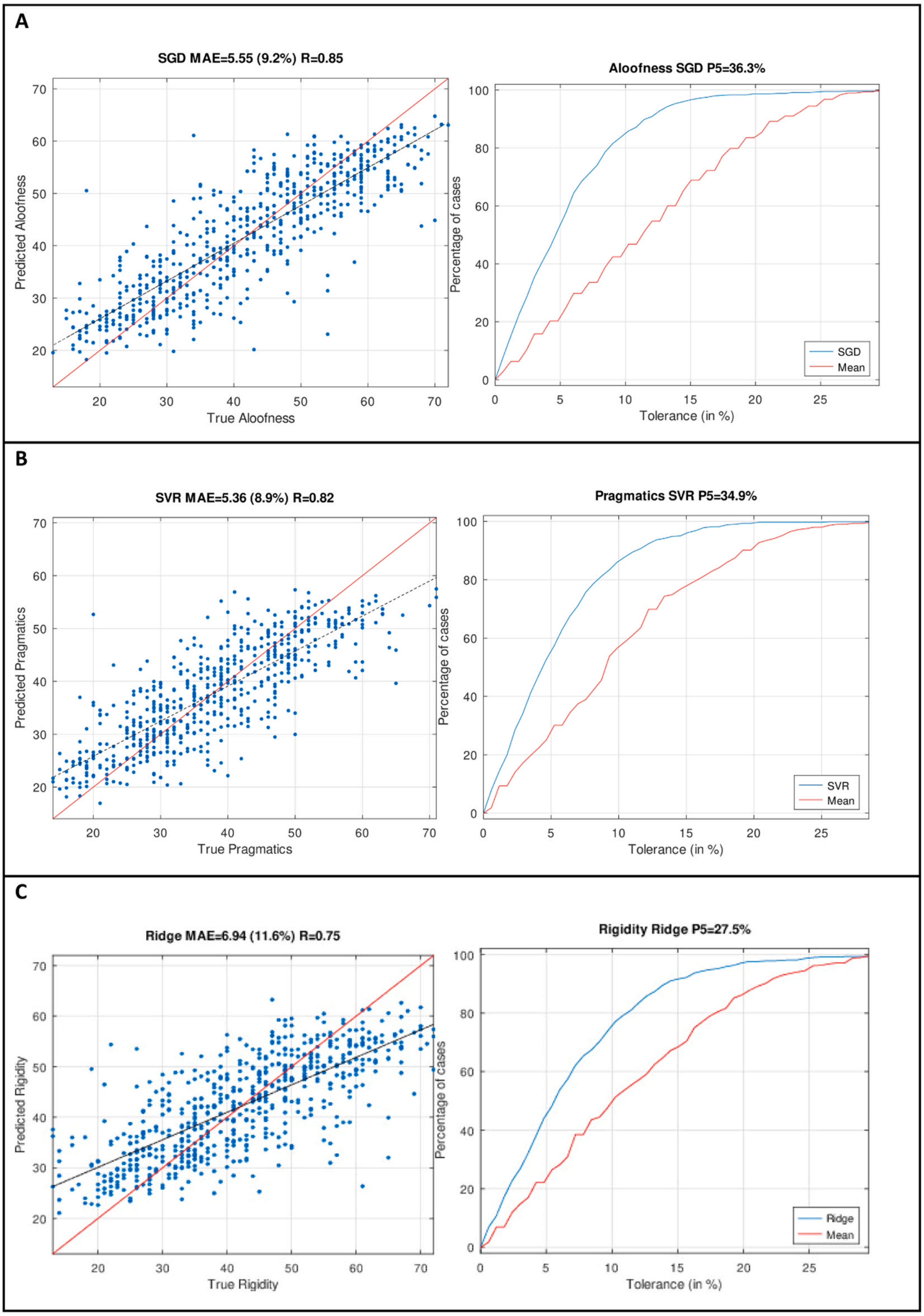

Fig. 2. True and Predicted Values (Left) and Tolerance Diagram (Right) for the Aloofness (A), Pragmatics (B), and Rigidity (C) Scores Using Stochastic Gradient Descent (SGD), Support Vector Regression (SVR) and Ridge.

a value between 14 and 26, but it will never approximate an extreme phenotype.

For example, since the Aloofness score ranges from 12 to 72 points, if a person's true score is 20, the algorithm would predict a value between 14 and 26, but it would never approximate an extreme phenotype.

Fig. 2B displayed the same plots corresponding to Pragmatics using SVR regressors. The left panel of Fig. 2B showed that accuracy on the prediction was similar to Aloofness, with good agreement between predicted and actual values (Fig. 2B left), although the trend line is farther than the red line than in Aloofness. The tolerance curve (Fig. 2B right) was closer to the left vertical axis than the red line, indicating high prediction accuracy. The P5 value of 34.9 % indicated that almost half of the data points deviated by less than 5 % of the range (57 points), which confirms a high prediction accuracy. While both Aloofness and Pragmatics showed strong correlations and low errors, Pragmatics had a lower MAE (5.36 vs 5.55), a lower MAPE (8.9 % vs 9.2 %), and a higher P5 (36.9 % vs 34.3 %). These metrics suggested that the model's predictions for Pragmatics were even more accurate and reliable than its predictions for Aloofness, despite a lower R (0.82 vs 0.85).

Fig. 2C showed that the predictive reliability for Rigidity was still good, but slightly lower compared to Aloofness and Pragmatics. While the predicted values followed the general trend of true values, deviations were more pronounced at the extremes. The blue curve in the tolerance diagram was also quite separated from the red one, but with a lower P5 value (27.5 %). Although lower than in the two previous cases, nearly one-third of the data deviated by less than 5 % of the range (60 points).

Fig. 3A and B displayed the corresponding plots for Depression and Anxiety, where the correlations were only moderate. In Fig. 3A and B (left) the predictive values no longer exhibited the increasing tendency "following" the true values that existed in the BAPQ

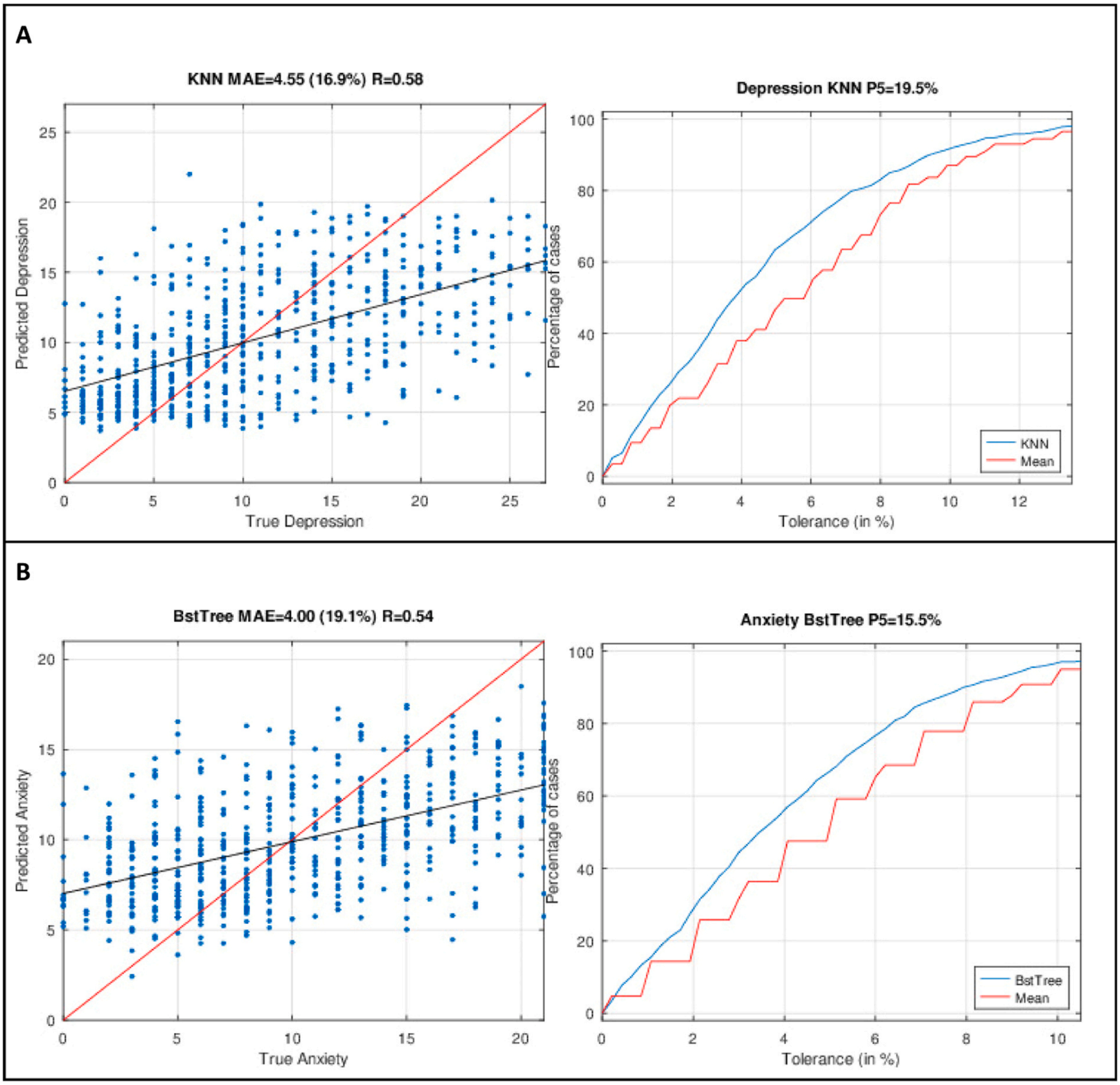

Fig. 3. True and Predicted Outputs and Tolerance Diagram for Depression Score (A) Using K-Nearest Neighbors (KNN) and for Anxiety Score (B) Using Boosting Ensemble of Regression Trees (BstTree).

scores, and the extreme (lower or higher) values were not predicted accurately in the left and right ends of the plots. Besides, the dashed trend lines are very far from the red line. The blue and red lines were nearby in the right panels, with only a small space between them, compared to Fig. 2. Thus, the best regressors (KNN for Depression and BstTree for Anxiety) were not much more reliable than the mean regressor. Moreover, the best regressor was only capable of predicting 19.5 % of participants within a 5 % tolerance for Depression and 15.5 %% for Anxiety (Fig. 3A and B right).

To test the influence of the input variables autism diagnosis and gender in the prediction, we repeated the above experiments:

1. Using all CAT-Q-ES individual items and gender as inputs to the regressor (rows 11–12 in Table 3).
2. Using all CAT-Q-ES individual items and autism diagnosis as inputs, but not gender (rows 14–15 in Table 3).
3. Using only CAT-Q-ES individual items, gender and autism diagnosis as inputs (rows 17–18 in Table 3).

The addition of gender or/and autism diagnosis did not alter the results. Specifically, for Aloofness, R remained constant (R=.85) and MAE reduced slightly from 5.55 to 5.53 (with gender), 5.54 (with autism diagnosis) and 5.54 (with both). For Pragmatics, R also increased slightly from.82 to.83, and MAE decreased up to four hundredths from 5.36 to 5.32 (gender), 5.29 (autism) and 5.31 (both); for Rigidity, R did not change, while MAE decreased from 6.94 to values between 6.84 and 6.92. For Depression R increased from.58 or.61, and MAE reduced from 4.55 to 4.52 (gender), 4.46 (autism) and 4.48 (both). Finally, for Anxiety R remained constant and reduced from.54 to.53 (gender), while MAE reduced from 4.00 to 3.98 (gender or autism) and 3.97 (both). These slight variations suggested that gender and autism diagnosis did not provide the regressor with extra information that was not already implicit in the CAT-Q-ES questionnaire items. Therefore, it is not necessary to explicitly provide the autism diagnosis to the regressor to make a reliable prediction.

Discussion

This study explored the viability of creating reliable predictive algorithms based on camouflaging behaviors to predict autistic traits and emotional comorbidities in a heterogeneous sample of autistic and non-autistic adults. Our findings showed that machine learning models based on self-reported camouflaging were reliable for predicting true values of autistic traits and anxiety and depression symptoms. However, the predictive algorithms for Anxiety and Depression achieved moderate correlations. Interestingly, gender and/or diagnosis status did not add information that improved the prediction's accuracy. The model can be applied even in cases where the diagnosis is unclear or not yet established, supporting the use of camouflaging measures as potential screening tools in neurodiverse populations.

The present findings aligned with extensive literature linking the camouflaging of autistic traits to poorer mental health in individuals who engaged in these strategies to a greater extent, regardless of their diagnosis (Cassidy et al., 2023; Cook et al., 2021; Lundin Remnélius et al., 2024; Milner et al., 2023; Somerville et al., 2024). In the present study, autistic participants presented more camouflaging behaviors, more autistic traits, and depression and anxiety symptomatology than non-autistic participants. Additionally, non-binary people also overscored other gender groups in all measures. This pattern is consistent with prior evidence suggesting that autistic individuals are more likely to not identify with their assigned-at-birth sex and that trans and non-binary individuals are more likely to exhibit autistic traits than cis-gender individuals (Walsh et al., 2018; Warrier et al., 2020). Our results regarding non-binary individuals self-reporting more anxiety and depression than women and males were in line with other studies about young adults (Alonzi et al., 2020).

The present study suggests that non-binary individuals camouflage more than other genders, including women and men. Similarly, McQuaid et al. (2022) found that gender-diverse autistic adults engaged in more camouflaging behaviors than cisgender autistic adults. Moreover, camouflaging has been identified as a predictor of stress and anxiety in trans and non-binary autistic adults (White et al., 2024). Yet, further research needs to determine whether trans/non-binary individuals rely on these strategies more frequently. It is also important to examine how this form of maladaptive coping affects their mental health compared to other genders.

The machine learning models developed in this work, once replicated, redefined and validated may support routine clinical practice. Current results indicated that models based on self-reported camouflaging behaviors can detect patterns associated with autistic traits even in individuals who have not received a diagnosis. The predictive models of the three BAPQ subscales exhibited a predictive accuracy of ±5 % of the true value for around 30 % of cases, equivalent to predicting scores within ±3 points. When increasing the tolerance from 5 % to 10 % of the range, we can predict the autistic trait score with a threshold of ±6 points in 75–85 % of cases with the information obtained with the CAT-Q-ES questionnaire. In clinical terms, this means the model can predict an indicative score on a dimension of the autistic phenotype with the risk of being wrong ±6 points, but never an extreme score. This score provided by the algorithm will allow clinicians to guide the assessment and personalised care of the patient based on their characteristics. Despite the promising results regarding autistic traits, Anxiety and Depression achieved a P5 values below 30 %, making the prediction less reliable. These models may serve clinical practitioners as a previous screening of potential subtle autistic profiles and emotional problems.

Literature has shown that machine learning models can be used to predict emotional outcomes and symptom progression in psychiatric disorders (Agne et al., 2022; Segalàs et al., 2024; Tubío-Fungueiriño et al., 2022, 2024), including co-occurring conditions in autism (Alateyat et al., 2022; Fernández-Delgado et al., 2024). Autistic adults, especially those with fewer support needs, often face long delays in obtaining a diagnosis. This delay, along with maladaptive coping strategies such as continuous camouflaging, can negatively impact their mental health. Alateyat et al. (2022) showed that anxiety and depression symptoms could be predicted from sensory profiles in autistic children and adolescents, highlighting the importance of early intervention. Similarly, detecting highly masked autistic traits alongside depression and anxiety symptoms by self-reported camouflaging may help clinicians recognize when psychological distress is rooted in prolonged undiagnosed autism and persistent masking behaviors. The developed algorithms presented moderate-strong correlations between true and predicted values for autistic traits, but the correlations were moderate regarding anxiety and depression. These results suggest that developing machine learning algorithms based on CAT-Q-ES scores may be a feasible option for a timely identification of autistic traits and emotional symptoms for individuals with masked or below the threshold autistic traits.

Machine learning algorithms, like the ones we have developed in this research should be extensively cross-validated using data from health records before considering their implementation in mental health care. Additionally, ethical concerns of applying predictive algorithms in mental health are relevant to be mentioned in this manuscript. Mental health professionals should be aware of unintentional reinforcement of stigma and the pathologization of (mal)adaptive social strategies like social camouflaging. Adapting one's behavior in social contexts—whether to avoid discrimination or to achieve personal goals—is not inherently pathological and does not necessarily indicate autism (Ai et al., 2022). Additionally, algorithmic models should be used as screeners to accelerate being derived for a deeper and personalized attention but never replace the clinical evaluation. Consequently, clinicians must apply these algorithms following a personalized medicine approach that considers autonomy and different aspects and contexts of patient daily life.

Limitations

This study had some limitations, the most notable being the over-representation of women in our sample. This imbalance may be explained by the fact that the data analyzed came from the Spanish validation of the CAT-Q, an instrument designed to help highly masked autistic adults, especially women. This may have accounted for the higher prevalence of women in the current sample, as online studies can be biased towards individuals with a specific interest in the topic (such as women), with greater cognitive abilities (Milner et al., 2023; Rødgaard et al., 2022), and a moderate to high socioeconomic status (Milner et al., 2023; Warriner & Miller, 2002).

Another limitation was the inability to ensure the accuracy of self-reported diagnoses of autism and other conditions by participants, potentially impacting the reliability of the results. To minimize this issue, participants were instructed to report only clinician-confirmed diagnoses and not to indicate a diagnosis based on personal feelings of distress. However, future studies may benefit from including clinician-based diagnosis to support the self-reported diagnosis and also observational methods that provide more information about camouflaging strategies and autistic traits.

While the autistic traits (measured with BAPQ) models achieved a high predictive accuracy, the results of models for anxiety and depression were more modest. This may be explained by the nature of the assessment tools used in the present study. The BAPQ covers three distinct autistic traits domains, each with several interrelated items reflecting different personality traits of each domain. In contrast, the PHQ-9 and GAD-7 are screening scales with items aligning with DSM-IV diagnostic criteria for MDD and GAD, respectively. Each item corresponds to a diagnostic criterion, contributing to greater variability in the dataset, as they capture diverse aspects (e.g., suicidal ideation or fatigue and/or loss of energy), leading to more scattered data and poorer predictive performance. Therefore, while the GAD-7 and PHQ-9 provide a general overview of anxiety and depression symptoms, the BAPQ subscales offer a more focused measure of specific autistic traits, leading to potentially more reliable and consistent data patterns. Finally, this study only considered symptoms of generalized anxiety and did not measure symptoms of other disorders, such as social anxiety, which has also been linked to autistic masking (Hull et al., 2021).

Considering this was the first study to test the viability of creating a machine learning algorithm to predict mental health outcomes and autistic traits using the CAT-Q, future studies should validate this tool using dimensional scales that measure anxiety and depression on a continuum, rather than screening tools that look at and categorize the presence and frequency of diagnostic criteria. This may reduce the scatter in scores and make the algorithm more effective in predicting specific patterns of traits or behaviors. Improving predictive models based on brief self-reported assessments of camouflaging strategies may provide early indicators of autistic traits, anxiety, and depressive symptoms in both autistic and non-autistic adults. Identifying these signs may facilitate referrals for comprehensive assessments, particularly in cases where camouflaging prevents individuals from meeting traditional diagnostic criteria. While this approach has the potential to shorten the diagnostic process—especially for women, who are often diagnosed later than males (Milner et al., 2023)—further research is needed to enhance its accuracy in predicting co-occurring affective symptoms and potentially preventing their progression into more severe psychiatric conditions.

Conclusion

This work explores the viability of creating reliable predictive algorithms based on camouflaging behaviors to predict autistic traits and emotional comorbidities in a heterogeneous sample of autistic and non-autistic adults. The present findings provide promising initial evidence that machine learning techniques can predict autistic traits and symptoms of anxiety and depression based on camouflaging behaviors in a neurodiverse sample. While the model shows acceptable accuracy for predicting autistic traits, it highlighted challenges in predicting anxiety and depression, indicating the need to improve the algorithm using dimensional scales. Despite these challenges, this research highlights the potential of the CAT-Q-ES questionnaire as a valuable tool for developing machine learning algorithms to predict autistic traits and anxiety-depression symptoms in adults where autism has not yet been detected. Given the results, there is potential for implementing predictive algorithms as screening tools to improve healthcare access. Validating and refining the present algorithm could further streamline timely referrals to specialized mental health services by identifying autistic traits and anxiety-depressive symptoms through a brief, self-administered assessment. Future work will also use unsupervised techniques to discover patterns in data, especially in certain individuals.

CRediT authorship contribution statement

Fernández Prieto Montse: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Fernández Delgado Manuel:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis. **Eva Cernadas:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Angel Carracedo:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition. **Pozo Rodríguez Marta:** Writing – review & editing, Investigation. **Tubío Fungueiriño María:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Sabela Conde-Pumpido Zubizarreta:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization.

Consent to participate

All participants read and accepted participation in this study and were informed that results of analyzing their data will be submitted for publication.

Ethics approval

This study is performed in line with the principles of the Declaration of Helsinki. The Ethics Committee of the University of Santiago de Compostela (Code: USC 26/2023) reviewed and approved the present study. The anonymity of the participants is preserved during data collection.

Funding

This work is supported by Fundación María José Jove. This investigation has received financial support from: Ministerio de Ciencia e Innovación, Instituto de Salud Carlos III (Spain) (PI22/00025), Reference Competitive Group accreditation 2022-2025, GRC (GI-1636); European Union (European Regional Development Fund - ERDF); and Xunta de Galicia (Centro de investigación de Galicia accreditation 2024-2027 ED431G-2023/04 and ED431G-2023/02). S.C-P.Z and M.P-R are supported by a predoctoral fellowship by Xunta de Galicia.

Declaration of Competing Interests

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

Acknowledgements

We are grateful to all patient associations, autism institutions, and federations that have contributed to this study and have been steadfast collaborators in research for an extended period.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.reia.2025.202712.

Data availability

Data will be made available on request.

References

Abdelhamid, N., Thind, R., Mohammad, H., & Thabtah, F. (2023). Assessing autistic traits in toddlers using a Data-Driven approach with DSM-5 mapping. *Bioengineering, 10*(10), 1131. https://doi.org/10.3390/bioengineering10101131

Agne, N. A., Tisott, C. G., Ballester, P., Passos, I. C., & Ferrão, Y. A. (2022). Predictors of suicide attempt in patients with obsessive-compulsive disorder: an exploratory study with machine learning analysis. *Psychological Medicine, 52*(4), 715–725. https://doi.org/10.1017/S0033291720002329

Ai, W., Cunningham, W. A., & Lai, M.-C. (2022). Reconsidering autistic 'camouflaging' as transactional impression management. *Trends in Cognitive Sciences, 26*(8), 631–645. https://doi.org/10.1016/j.tics.2022.05.002

Ai, W., Cunningham, W. A., & Lai, M.-C. (2023). The dimensional structure of the camouflaging autistic traits questionnaire (CAT-Q) and predictors of camouflaging in a representative general population sample. *Comprehensive Psychiatry, 128*, Article 152434. https://doi.org/10.1016/j.comppsych.2023.152434

Alateyat, H., Cruz, S., Cernadas, E., Tubío-Fungueiriño, M., Sampaio, A., González-Villar, A., Carracedo, A., Fernández-Delgado, M., & Fernández-Prieto, M. (2022). A machine learning approach in autism spectrum disorders: from sensory processing to behavior problems. *Frontiers in Molecular Neuroscience, 15*. https://doi.org/10.3389/fnmol.2022.889641

Allison, C., Auyeung, B., & Baron-Cohen, S. (2012). Toward brief "red flags" for autism screening: the short autism spectrum quotient and the short quantitative checklist in 1,000 cases and 3,000 controls. *Journal of the American Academy of Child Adolescent Psychiatry, 51*(2), 202–212.e7. https://doi.org/10.1016/j.jaac.2011.11.003

Alonzi, S., La Torre, A., & Silverstein, M. W. (2020). The psychological impact of preexisting mental and physical health conditions during the COVID-19 pandemic. *Psychological Trauma, 12*(S1), S236–S238. https://doi.org/10.1037/tra0000840

Alpaydın, E. (2020). *Introduction to Machine Learning* (4th ed.). The MIT Press.

American Psychiatric Association. (1994). *Diagnostic and statistical manual of mental disorders* (4th ed.).

Beck, J. S., Lundwall, R. A., Gabrielsen, T., Cox, J. C., & South, M. (2020). Looking good but feeling bad: 'Camouflaging' behaviors and mental health in women with autistic traits. *Autism, 24*(4), 809–821. https://doi.org/10.1177/1362361320912147

Botha, M., & Frost, D. M. (2020). Extending the minority stress model to understand mental health problems experienced by the autistic population. *Society and Mental Health, 10*(1), 20–34. https://doi.org/10.1177/2156869318804297

Bouzy, J., Brunelle, J., Cohen, D., & Condat, A. (2023). Transidentities and autism spectrum disorder: a systematic review. *Psychiatry Research, 323*, Article 115176. https://doi.org/10.1016/j.psychres.2023.115176

Cassidy, S., McLaughlin, E., McGranaghan, R., Pelton, M., O'Connor, R., & Rodgers, J. (2023). Is camouflaging autistic traits associated with defeat, entrapment, and lifetime suicidal thoughts? Expanding the integrated motivational volitional model of suicide. *Suicide LifeThreatening Behavior, 53*(4), 572–585. https://doi.org/10.1111/sltb.12965

Chew, D., Tollit, M. A., Poulakis, Z., Zwickl, S., Cheung, A. S., & Pang, K. C. (2020). Youths with a non-binary gender identity: a review of their sociodemographic and clinical profile. *The Lancet Child Adolescent Health, 4*(4), 322–330. https://doi.org/10.1016/S2352-4642(19)30403-1

Colton, T. (1974). *Statistics in medicine*. Boston (MA): Little Brown and Co.

Conde-Pumpido Zubizarreta, S., Lois-Mosquera, M., Tubío-Fungueiriño, M., Alemany-Navarro, M., Hull, L., Carracedo, A., Gándara-Gafo, B., & Fernández-Prieto, M. (2025). Camouflaging autistic traits questionnaire: cultural adaptation, reliability, and validity in autistic and Non-Autistic from Spain. *Autism in Adulthood*. https://doi.org/10.1089/aut.2024.0003

Cook, J., Hull, L., Crane, L., & Mandy, W. (2021). Camouflaging in autism: a systematic review. *Clinical Psychology Review, 89*, Article 102080. https://doi.org/10.1016/j.cpr.2021.102080

Fernández-Delgado, M., Cruz, S., Cernadas, E., Alateyat, H., Tubío-Fungueiriño, M., Sampaio, A., Carracedo, A., & Fernández-Prieto, M. (2024). Population-based detection of children ASD/ADHD comorbidity from atypical sensory processing. *Applied Intelligence, 54*(20), 9906–9923. https://doi.org/10.1007/S10489-024-05655-Z

Fernández-Delgado, M., Sirsat, M. S., Cernadas, E., Alawadi, S., Barro, S., & Febrero-Bande, M. (2019). An extensive experimental survey of regression methods. *Neural Networks, 111*, 11–34. https://doi.org/10.1016/j.neunet.2018.12.010

Cruz, S., Zubizarreta, S. C., Costa, A. D., Araújo, R., Martinho, J., Tubío-Fungueiriño, M., … Fernández-Prieto, M. (2024). Is there a bias towards males in the diagnosis of autism? A systematic review and Meta-Analysis. *Neuropsychology Review, 35*(1), 153–176. https://doi.org/10.1007/s11065-023-09630-2

Dell'Osso, L., Cremone, I. M., Muti, D., Massimetti, G., Lorenzi, P., Carmassi, C., & Carpita, B. (2022). Validation of the Italian version of the camouflaging autistic traits questionnaire (CAT-Q) in a university population (Advance online publication) *Comprehensive Psychiatry, 114*, Article 152295. https://doi.org/10.1016/j.comppsych.2022.152295.

Diez-Quevedo, C., Rangil, T., Sanchez-Planell, L., Kroenke, K., & Spitzer, R. L. (2001). Validation and utility of the patient health questionnaire in diagnosing mental disorders in 1003 general hospital spanish inpatients. *Psychosomatic Medicine, 63*(4), 679–686. https://doi.org/10.1097/00006842-200107000-00021

Hake, R. (2024). Autistic trans camouflaging: an early phenomenological exploration. *Philosophical Psychology, 38*(1), 150–167. 〈https://doi-org.ezbusc.usc.gal/10.1080/09515089.2024.2385056〉.

García-Campayo, J., Zamorano, E., Ruiz, M. A., Pardo, A., Pérez-Páramo, M., López-Gómez, V., Freire, O., & Rejas, J. (2010). Cultural adaptation into spanish of the generalized anxiety disorder-7 (GAD-7) scale as a screening tool. *Health and Quality of Life Outcomes, 8*, 8. https://doi.org/10.1186/1477-7525-8-8

Godoy-Giménez, M., González-Rodríguez, A., Cañadas, F., Estévez, A. F., & Sayans-Jiménez, P. (2018). Psychometric properties of the spanish version of the broad autism phenotype questionnaire: strengths, weaknesses, and future improvements. *Journal of Autism and Developmental Disorders, 48*(3), 770–783. https://doi.org/10.1007/s10803-017-3438-0

Harris, P. A., Taylor, R., Minor, B. L., Elliott, V., Fernandez, M., O'Neal, L., McLeod, L., Delacqua, G., Delacqua, F., Kirby, J., Duda, S. N., & REDCap Consortium. (2019). The REDCap consortium: building an international community of software platform partners. *Journal of Biomedical Informatics, 95*, Article 103208. https://doi.org/10.1016/j.jbi.2019.103208

Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., & Conde, J. G. (2009). Research electronic data capture (REDCap)–a metadata-driven methodology and workflow process for providing translational research informatics support. *Journal of Biomedical Informatics, 42*(2), 377–381. https://doi.org/10.1016/j.jbi.2008.08.010

Hobson, H. M., & Lee, A. (2023). Camouflaging in Developmental Language Disorder: The Views of Speech and Language Pathologists and Parents. *Communication Disorders Quarterly, 44*(4), 247–256. https://doi.org/10.1177/15257401221120937

Hull, L., Levy, L., Lai, M.-C., Petrides, K. V., Baron-Cohen, S., Allison, C., Smith, P., & Mandy, W. (2021). Is social camouflaging associated with anxiety and depression in autistic adults? *Molecular Autism, 12*(1), 13. https://doi.org/10.1186/s13229-021-00421-1

Hull, L., Mandy, W., Lai, M.-C., Baron-Cohen, S., Allison, C., Smith, P., & Petrides, K. V. (2019). Development and validation of the camouflaging autistic traits questionnaire (CAT-Q). *Journal of Autism and Developmental Disorders, 49*(3), 819–833. https://doi.org/10.1007/s10803-018-3792-6

Hurley, R. S. E., Losh, M., Parlier, M., Reznick, J. S., & Piven, J. (2007). The broad autism phenotype questionnaire. *Journal of Autism and Developmental Disorders, 37*(9), 1679–1690. https://doi.org/10.1007/s10803-006-0299-3

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: validity of a brief depression severity measure. *Journal of General Internal Medicine, 16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Lorenz, S., & Hull, L. (2024). Do all of us camouflage? Exploring levels of camouflaging and mental health well-being in the general population. *Trends in Psychology*, 1–15. https://doi.org/10.1007/s43076-024-00357-4

Lundin Remnélius, K., & Bölte, S. (2023). Camouflaging in autism: age effects and Cross-Cultural validation of the camouflaging autistic traits questionnaire (CAT-Q). *Journal of Autism and Developmental Disorders*. https://doi.org/10.1007/s10803-023-05909-8

Lundin Remnélius, K. L., Neufeld, J., Isaksson, J., & Bölte, S. (2024). Does camouflaging cause reduced quality of life? A Co-Twin control study. *Journal of Autism and Developmental Disorders*. https://doi.org/10.1007/s10803-024-06583-0

McQuaid, G. A., Lee, N. R., & Wallace, G. L. (2022). Camouflaging in autism spectrum disorder: examining the roles of sex, gender identity, and diagnostic timing. *Autism The International Journal of Research and Practice, 26*(2), 552–559. https://doi.org/10.1177/13623613211042131

Milner, V., Colvert, E., Hull, L., Cook, J., Ali, D., Mandy, W., & Happé, F. (2023). Does camouflaging predict age at autism diagnosis? A comparison of autistic men and women, 10.1002/aur.3059. Advance online publication *Autism Research*. https://doi.org/10.1002/aur.3059.

Milner, V., Mandy, W., Happé, F., & Colvert, E. (2023). Sex differences in predictors and outcomes of camouflaging: comparing diagnosed autistic, high autistic trait and low autistic trait young adults. *Autism, 27*(2), 402–414. https://doi.org/10.1177/13623613221098240

Moore, H. L., Cassidy, S., & Rodgers, J. (2024). Exploring the mediating effect of camouflaging and the moderating effect of autistic identity on the relationship between autistic traits and mental wellbeing. *Autism Research Official Journal of the International Society for Autism Research, 17*(7), 1391–1406. https://doi.org/10.1002/aur.3073

Murphy, K. P. (2012). *Machine learning: a probabilistic perspective*. MIT Press.

Nishiyama, T., & Kanne, S. M. (2014a). On the misapplication of the BAPQ in a study of autism. *Journal of Autism and Developmental Disorders, 44*(8), 2079–2080. https://doi.org/10.1007/s10803-014-2077-y

Nishiyama, T., Suzuki, M., Adachi, K., Sumi, S., Okada, K., Kishino, H., Sakai, S., Kamio, Y., Kojima, M., Suzuki, S., & Kanne, S. M. (2014b). Comprehensive comparison of Self-administered questionnaires for measuring quantitative autistic traits in adults. *Journal of Autism and Developmental Disorders, 44*(5), 993–1007. https://doi.org/10.1007/s10803-013-2020-7

Peachey, M., & Crane, L. (2024). I Don't understand their sense of Belonging": Exploring how nonbinary autistic adults experience gender. *Autism in Adulthood, 6*(4), 462–473. https://doi.org/10.1089/aut.2023.0071

Perry, E., Mandy, W., Hull, L., & Cage, E. (2022). Understanding camouflaging as a response to Autism-Related stigma: A social identity theory approach. *Journal of Autism and Developmental Disorders, 52*(2), 800–810. https://doi.org/10.1007/s10803-021-04987-w

Rajab, K. D., Padmavathy, A., & Thabtah, F. (2021). Machine learning application for predicting autistic traits in toddlers. *Arabian Journal for Science and Engineering, 46*(4), 3793–3805. https://doi.org/10.1007/s13369-020-05165-3

Robeson, M., Brasil, K. M., Adams, H. C., & Zlomke, K. R. (2024). Measuring depression and anxiety in autistic college students: A psychometric evaluation of the PHQ-9 and GAD-7. *Autism, 28*(11), 2793–2805. https://doi.org/10.1177/13623613241240183

Rødgaard, E.-M., Jensen, K., Miskowiak, K. W., & Mottron, L. (2022). Representativeness of autistic samples in studies recruiting through social media. *Autism Research, 15*(8), 1447–1456. https://doi.org/10.1002/aur.2777

Somerville, M., MacPherson, S. E., & Fletcher-Watson, S. (2024). The associations between camouflaging, autistic traits, and mental health in nonautistic adults. *Autism in Adulthood, 6*(1), 106–113. https://doi.org/10.1089/aut.2023.0018

Segalàs, C., Cernadas, E., Puialto, M., Fernández-Delgado, M., Arrojo, M., Bertolin, S., Real, E., Menchón, J. M., Carracedo, A., Tubío-Fungueiriño, M., Alonso, P., & Fernández-Prieto, M. (2024). Cognitive and clinical predictors of a long-term course in obsessive compulsive disorder: A machine learning approach in a prospective cohort study. *Journal of Affective Disorders, 350*, 648–655. https://doi.org/10.1016/j.jad.2024.01.157

Sellamuthu, S., & Rose, S. (2024). Enhanced special needs assessment: A multimodal approach for autism prediction. *IEEE Access, 12*, 121688–121699. https://doi.org/10.1109/ACCESS.2024.3453440

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine, 166*(10), 1092–1097. https://doi.org/10.1001/archinte.166.10.1092

Tubío-Fungueiriño, M., Cernadas, E., Fernández-Delgado, M., Arrojo, M., Bertolin, S., Real, E., Menchon, J. M., Carracedo, A., Alonso, P., Fernández-Prieto, M., & Segalàs, C. (2024). Prediction of pharmacological response in OCD using machine learning techniques and clinical and neuropsychological variables. S2950-2853(24)00070-X. Advance online publication *Spanish Journal of Psychiatry and Mental Health*. https://doi.org/10.1016/j.sjpmh.2024.11.001.

Tubío-Fungueiriño, M., Cruz, S., Sampaio, A., Carracedo, A., & Fernández-Prieto, M. (2021). Social camouflaging in females with autism spectrum disorder: a systematic review. *Journal of Autism and developmental Disorders, 51*(7), 2190–2199. https://doi.org/10.1007/s10803-020-04695-x

van der Putten, W. J., Mol, A. J. J., Groenman, A. P., Radhoe, T. A., Torenvliet, C., van Rentergem, J. A. A., & Geurts, H. M. (2024). Is camouflaging unique for autism? A comparison of camouflaging between adults with autism and ADHD. *Autism Research, 17*(4), 812–823. https://doi.org/10.1002/aur.3099

Walsh, R. J., Krabbendam, L., Dewinter, J., & Begeer, S. (2018). Brief report: gender identity differences in autistic adults: associations with perceptual and Socio-cognitive profiles. *Journal of Autism and Developmental Disorders, 48*(12), 4070–4078. https://doi.org/10.1007/s10803-018-3702-y

Warrier, V., Greenberg, D. M., Weir, E., Buckingham, C., Smith, P., Lai, M.-C., Allison, C., & Baron-Cohen, S. (2020). Elevated rates of autism, other neurodevelopmental and psychiatric diagnoses, and autistic traits in transgender and gender-diverse individuals. *Nature Communications, 11*(1), 3959. https://doi.org/10.1038/s41467-020-17794-1

Warriner, G. K., & Miller, S. (2002). Evaluating Socio-economic status (SES) bias in survey nonresponse. *Journal of Official Statistics, 18*(1), 1. ⟨https://www.proquest.com/scholarly-journals/evaluating-socio-economic-status-ses-bias-survey/docview/1266793999/se-2⟩.

White, L. C. J., Ixqe, K. V., Goodall, K., & Gillespie-Smith, K. (2024). Minority stress, camouflaging, and mental health outcomes in transgender and/or non-binary autistic adults (Advance online publication) *Autism in Adulthood*, 1–15. https://doi.org/10.1089/aut.2023.0151.

Wicherkiewicz, F., & Gambin, M. (2024). Relations between social camouflaging, life satisfaction, and depression among polish women with ADHD, 10.1007/s10803-024-06410-6. Advance online publication *Journal of Autism and Developmental Disorders*. https://doi.org/10.1007/s10803-024-06410-6.

Zhu, F. L., Wang, S. H., Liu, W. B., Zhu, H. L., Li, M., & Zou, X. B. (2023). A multimodal machine learning system in early screening for toddlers with autism spectrum disorders based on the response to name. *Frontiers in Psychiatry, 14*, Article 1039293. https://doi.org/10.3389/fpsyt.2023.1039293