Bias In Machine Learning Applications In Psychiatry

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1 Abstract

The integration of machine learning (ML) into psychiatric practice offers benefits in diagnosis and treatment prediction, but it also creates challenges related to bias. Unlike physical healthcare, psychiatric diagnoses rely on subjective assessments and patient-reported symptoms, introducing complexities in applying ML models to diagnosis as well as treatment.

This paper examines the potential biases in two specific ML applications in psychiatry: suicide prediction and autism assessment. Drawing on existing psychological research on bias in these domains, it highlights biases in psychiatric diagnoses, particularly concerning ethnicity and gender. The first case study explores a suicide prediction model using electronic health record data which might adopt and enhance racial biases in risk scores. The second case study focuses on an observation-based classifier for autism, emphasizing the gender bias inherent in diagnostic tools like the Autism Diagnostic Observation Schedule (ADOS). The results of the analysis support how important it is to consider existing biases in psychiatric concepts when developing ML applications.

2 Introduction

The utilization of machine learning (ML) models in healthcare and medical settings has given us new opportunities for diagnostic precision and treatment prediction. Especially for physical healthcare, the objectivity of methods, such as imaging and biomarkers, enables the evaluation of model performance against human doctors. However, this is different in psychiatric healthcare, where the diagnosis and treatment is not as straightforward in to comparison physical health contexts.

For example, imaging, biomarkers etc. show very concrete illness markers and how they develop through certain treatment. In psychiatric practice, however, finding diagnosis and treatment is based on psychological factors and depends on human evaluation. Not only is the diagnosis therefore influenced by the subjectivity of the assessment of the doctor, but also on the content of the patient´s report of symptoms. Additionally, cultural norms and historical factors are relevant influences in definition and classification of different disorders. Since diagnoses hinge on subjective client descriptions and feedback, the potential for distortions in diagnostic assessments across different demographic groups is also heightened.

This brings benefits and risks of applying ML methods in the field of psychiatry: on one hand using machine learning in neuro-imaging could enhance the objectivity of diagnosis processes since ML models could find more specific differences in brain functions of mentally ill patients than the human eye. On the other hand, especially in methods based on questionnaire and behavioral data, bias that already exists in the field of psychiatry might be reflected and amplified when training ML models with them.

The stakes in psychiatric ML applications are particularly high seeing as errors in diagnosis or treatment predictions can have severe and lasting effects on patients. While ML therefore offers an opportunity to improve clinical processes and introduce objectivity, there is a risk of maintaining existing biases into these models. Therefore, many researchers have already noted that reflection on bias in ML models in psychiatry is relevant as well as necessary and introduced the theoretical basis to controlling biases. (see e.g. (4))

Previous studies, such as that conducted by Obermeyer et. al. (1), have also already shed light on the biased outcomes of AI algorithms in physical healthcare, revealing differences in health risk scores that disadvantage Black patients compared to their White counterparts.

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Looking at bias in applications of ML models in psychiatry bias is relevant in the following respects. Firstly, we can find historical and socio-cultural bias in psychiatric data. Psychological research has been crafted and evaluated primarily for privileged white and western groups of people. This has led to a deficiency in socio-cultural sensitivity of diagnosis criteria, inclusiveness, and adaptability in our treatments. (2) New technological solutions are, however, often especially created to treat more people and such who do not usually access mental health services. (3) Therefore, it is especially important to check for bias in AI applications and how models can reinforce and sustain past societal disparities - since otherwise these solutions continue to discriminate or even amplify biased access and treatment to certain people and groups. Building ML models for psychiatry could therefore create a feedback loop in which biased models lead to more biased data.

Additionally, unbalanced samples or choosing features based on only one patient group can introduce representational bias when training the models. They are then discriminating against certain groups which, for example, need different features representations to assess their diagnosis, risk scores or medication success.

There are different ways in which machine learning has already been applied in psychiatry which are sensitive to bias. These different areas include diagnosis and classification, prediction of the course of illness, treatment through interventions and monitoring. (3)

In this paper I want to look at two specific examples of these types of application, specifically in the field of diagnosis and prediction.

I will focus on concepts which provide sufficient knowledge from psychological research how biased our classification of diagnosis and assessment potentially are. This will be used to reflect how this knowledge is relevant for the ML models, how they should be developed or assessed and adapted.

For example, with more research coming up on autism in females and shifting towards a less gender biased diagnosis, utilizing machine learning models in this field could be a chance to consider and include more variability. This is why one of the studies to be analyzed is on autism assessment with ML.

The other study will focus on suicide prediction with a ML model and I will look at how racial bias in psychiatric diagnosis could influence the bias in this prediction of suicidal behavior.

By investigating and critiquing these cases, I seek to contribute to a nuanced understanding of the challenges and opportunities presented by ML applications in psychiatric settings and to inform strategies for mitigating bias in future developments.

3 Related Work

Different works have analyzed the relevant principles for avoiding bias in machine learning methods.

Timmons et. al. (3) have analyzed areas in which AI can find implementation in the mental health fields as well as therefore can be influenced by the bias of AI. These areas include diagnosis, intervention, engagement, maintanance monitoring and prediction.

I will exemplary look at works in two of these areas in which machine learning models were utilized in the fields of diagnosis and prediction and analyze different possible bias in these studies.

Tay et. al. (4) provide different types of bias which can occur in this field of research: There can be bias in elements like ground truth, platform-based construct, behavioral expression, and feature computing. Similarly, algorithm-training bias may emerge during the development of algorithms when there is a lack of equivalence in the connection between extracted features and the ground truth. They state that one big limitation in the research is the absence of clear methodological guidelines. They also differentiate measurement bias from socio-cognitive bias, which involves errors in human cognitive judgments or attributions. Measurement bias is characterized by a distinct relationship between the latent score (i.e., psychological construct score) and the predicted observed score.

Since many studies do not analyze which socio-cognitive bias is relevant for ML models or their measurement bias for different subgroups I will focus on how certain studies should analyze subgroups to find potential differences between prediction and what has been found in psychological research as differences and bias between different groups. I will therefore focus on the influence of socio-cognitive bias on applying ML for e.g. diagnosis and induces measurement bias.

There is only limited work in which researchers analyze concrete ML model results for their bias. For example, Mosteiro et.al. (5) have developed a machine learning model predicting future benzo-

diazepine administrations, revealing unexpected gender-related bias and analyzed potential bias-mitigation strategies. In many existing projects using ML in psychiatry researchers do not, however, analyze datasets regarding their potential for bias and how the model performs for different groups. This is why in the following I will critique how certain studies should be analyzed regarding potential sources of bias.

4 Machine Learning for predicting suicidal behavior, racial bias and bias against minorities

4.1 Method and results

In their study Barak-Corren et. al. (6) tested the application of machine learning to predict suicidal behavior for patients based on various medical and demographic backgrounds. They used EHR data from medical centers in Boston and defined suicidal behavior through the ICD-9 diagnostic codes.

Naive Bayesian classifier models were utilized to assess individual suicide risks based on independent input variables such as demographic characteristics, diagnostic codes, laboratory results (normal/low/high), and prescribed medications (true/false values). They had a control group of patients without suicidal behavior for which they analyzed data from the entire observed time periods - in contrast, for the case group, the group of patients with suicidal behavior, they analyzed data from before the first suicidal event. Also, the separated the female from the male patient data and build two separate models for men and women which therefore minimizes gender bias in this model.

For the model training they assigned each independent input variable (e.g., diagnoses, medications, etc.) a risk score based on the ratio of its occurrence among patients with suicide attempts compared to the control group patients. Each patient had a risk score at each time point and with the model partial risk scores were calculated for each variable. To interpret the patient's score, they utilized the predefined thresholds selected during the training phase to achieve 90 percent and 95 percent specifities for each of which the sensitivity and timeliness of prediction were assessed.

Relevant results were that the model detected 44 percent of suicides among men and 46 percent of suicides among women at a 90 percent specificity level and was therefore more successful than models only using bivariate combinations of the accepted risk factors of depression, substance abuse and other mental disorders. Furthermore, using the model for even more specific subcategories such as specific age groups (e.g. women aged 45–65) performed better with 54 percent sensitivity.

Important risk factors in the model are personality disorders as well as bipolar disorder which were 7–10 times more common among case subjects compared to the control group. Also, opioid abuse had a 16 times higher likelihood among the case group.

4.2 Bias in psychological research

To assess which influences could bring bias in the developed model we have to look at how the variables used in the model are known to be biased among different groups. Especially diagnosis of disorders, but also the received type of medication differ between ethnicities. Additionally, the way people from different groups access professional psychiatric help differs.

Firstly, regarding diagnosis of personality disorders there is evidence that e.g. people with African Caribbean ethnicity are less likely to be diagnosed properly with a personality disorder with differing rates in different personality disorders. Especially high is the bias for example for anti-social personality disorders. (7)

In patients with bipolar disorder, racial bias leads to misdiagnosis of schizophrenia instead of mania with psychotic features in African American patients. (8) Additionally, treatment of African Americans is less likely to include anti-psychotic medication, but more likely to be treated with mood stabilizers such as lithium. (8)

Also, when having co-morbid disorders to a substance abuse disorder, White patients are more likely to be diagnosed and treated for these co-morbid disorders. Garb et. al. (7) write, for example: "Compared to Whites, Blacks with these co-morbid disorders were significantly less likely to receive services for mood or anxiety, equally likely to receive services for alcohol use disorders, and more likely to receive services for drug use disorders."

Anderson et. al. (9) investigates differences between races in responses of adolescences in suicide-related psychiatric assessments and noted that previous research has not explored the possibility of non-response, even though evidence suggests that individuals with higher levels of suicidality may be

less willing to disclose such information. (9) While there were less significant differences for questions about suicide plans, there was a statistically significant relationship between race and the response rate to questions about suicide attempts. African American students stood out in terms of non-response. Nearly 20 percent of African American adolescents omitted the question about suicide attempts, while only 7.6 percent of Caucasian youth omitted this item. (9)

Additionally, Rockett et. al. (13) investigated potential for misclassification of suicide for different ethnicities and found that Blacks and Hispanics had higher potential suicide misclassification relative to Whites.

Bommersbach et. al. (**?**) similarly found that patients with Black and Hispanic ethnicity were less likely than While individuals to report suicidal ideation, however more likely to report a suicide attempt. They also found that among people with suicidal ideation, for Black adults the likelihood of also having a suicidal attempt is higher than for White people. This indicates that that stigma is higher or help-seeking behavior lower in the group of Black people leading to them reaching a more severe health state when receiving help.

Lastly, there we can find an interaction between different demographic factors such as age and race regarding suicide: Garlow et. al. (12) showed the median age of patients who attempted suicide was more than a decade lower for black patients with 34 years compared to white patients with 44 years.

4.3 Analysis of Bias in ML model

While suicide rates among White people in the US remain higher than the ones among Black as well as Asian Pacific and Hispanic people, increases of suicide rate from 2018 to 2019 were higher for the latter while number of suicides reduced for White people. (11) This highlights the need to have especially sensitive early prediction of suicide among populations of non-White people.

However, we can find different way in which the model by Barak-Corren et. al. might neglect sensitivity towards differences between different race groups.

Firstly, when analyzing the dataset used to train the model in regards to racial equality we notice unbalanced sampling since the dataset has unequal ratios of various ethnicities with the majority of patients being white. (6)

If however, as we have seen, risk factors and medical records might differ between different ethnicities, this can lead to inaccurate or inefficient associations between other risk factors and ethnicity and mix different risk profiles.

In general, cause of a lack of number of patients with other ethnicities than White to compare suicide risk factors between groups might be the mentioned misclassification of suicide in some ethnicities. Also, we know from Anderson et. al. (9) that there might be differences in disclosure of suicide attempts of Black patients - therefore the number of unrecorded cases of unsuccessfully suicide attempts might also be lower for this population group. In predicting suicide the risk of Black patients might therefore be underestiamted.

However, in this study we can find a different sampling problem. The features the model uses in suicide prediction include demographic data as well as medical data about diagnosises, laboratory results and medications. The demographic data also includes ethnicity of the patient and one might suspect it to therefore influence the suicide risk assessment through suicide rates being higher for White people. However, the model results in higher risk scores for African Americans with 1.63 for men and 1.29 for women as well as Hispanic men with 1.43 and Hispanic women with 1.69 compared to Caucasian patients with 0.99 for both men and women. This leads us to discover another imbalance in the dataset used to train the model: While for the case and control group the ratio of White patients to other ethnicities is similar, the percentage of Hispanic and African American patients compared to other ethnicities in the case group is higher than in the control group.

However, this does not represent the ratios of the general population: While Hispanic and African American people make up 7.4 and 6.4 percent of the control group, the make up 12.3 and 8.3 percent of the case group. This can explain why suicide risk is higher for these ethnicities in the model than it would be based on population wide suicide risks. For the US population overall, suicide rate for Hispanic and Black individuals are 7.3 and 7.4 per 100.000 compared to 17.6 in 100.00 for White individuals. (11)

Reason for the imbalance in the dataset from the hospitals might be that - as we could conclude from Bommersbach et. al. (10) - Black and Hispanic people seek help when their health state is more severe, when they had a suicidal attempt and not "only" suicidal ideation. There might therefore be

a higher percentage of case subjects than control subjects from these ethnicities.

While it might therefore seem like the model makes up for bias in suicide assessment and classification since risk scores are lower for White patients, the cause of this might be the sample choice and imbalance. We can ask how risk scores would be different when trained on different datasets with different ratios and how the model can be applied to groups with different ratios of ethnicities.

Not only could the risk scores for certain ethnicities be influenced by the ethnicity´s percentage in the sample groups but also through interaction with other features. On one hand, seemingly objective medical data can, as analyzed, include bias which is perpetuated in the model. On the other, the risk scores of certain factors might be different for different ethnicities and we should pay attention how these differences should be accounted for in the model.

For example, the model calculated especially high risk scores for personality disorders, bipolar disorder and opioid abuse. (6) We also know that diagnosis of personality disorders, bipolar and co-morbid disorders to substance abuse are affected by racial bias in psychiatry which could lead to false increases as well as decreases of the risk score in the ML model. Therefore, if, for example, the group of African American people is not correctly diagnosed with bipolar, but instead with schizophrenia, their risk scores might be different for different disorders - similarly for African Caribbean patients not being correctly diagnosed with personality disorders. Also, if their substance abuse disorder is not correctly co-diagnosed with other disorders as well as not treated properly, their risk scores for substance abuse might be different. Since medication is also a feature in the model, bias through wrong or missing diagnosis and treatment has a second influence on the risk prediction for different ethnicities.

All of this can lead to higher lower risk scores for certain ethnicities because of different diagnosis patterns and co-morbidities or less diagnosises overall. It could also lead to higher risk scores through incorrect diagnosis of disorders or different medication.

It should therefore be taken into account that there are interactions of different risk factors, not only between, for example, suicide risk and race itself, but also through racial bias in other features. As an additional example we have also noted age differences in suicide attempts for different ethnicities. For that reason having more specific subgroups for age and race might result in more accurate prediction. The fact that the model already performed better when choosing specific age groups for women and men (6), is a sign that even more specification might be a valuable practice.

Just like there were two different models trained for female vs. male individuals, it might also make sense to train for different ethnicities or - first of all - test their the predictions for groups of different ethnicities to analyze limitations of applying this model to different demographics. Then different specifications and combinations of age groups, ethnicities etc. can be tested to see which lead to higher performance.

5 Machine Learning for autism and gender bias

5.1 Method and results

In their study Duda et. al. (14) develop a machine-learning classifier for differentiating cases of autism spectrum disorder (ASD) from non-spectrum. They use an observation-based classifier (OBC) which holds eight behaviors, namely frequency of vocalization directed to others, eye contact, social smile, shared enjoyment in interaction, showing, initiation of joint attention, functional play with objects, imagination/creativity. It calculates a score through an Alternating Decision Tree algorithm to assess a patient´s class (spectrum or non-spectrum) and also gives back the confidence level of the classification. The scores were compared to patient´s ADOS (Autism Diagnostic Observation Schedule) scores as a common autism diagnostic instrument to calculate sensitivity and specificity and the correlation of classification outcomes of the OBC and ADOS (using Spearman rank correlation).

Comparing to two version of ADOS, ADOS-G and ADOS-2, the OBC hat a sensitivity of >97 percent for both and a specificity of 77 percent for ADOS-G and 84 percent for ADOS-2. (14) The OBC results also had significant correlation to the ADOS-2 comparison score, so the authors concluded that the OBC reflects severity of the autism phenotype and that the OBC is a possibility for rapid classification to shorten waiting times for autism diagnosis. (14)

5.2 Bias in psychological research

Autism Spectrum Disorder presents - as the name suggests - as a wide spectrum of symptoms and severity levels. However, a lot of varieties and differences between groups have been a topic of research only in recent years: ASD has been considered a dominantly "male" disorder with 4:1 percent of diagnosed people being male compared to female. (15) In research on autism there has however been a sampling bias through, for example majority of the studied patients being male and most studies ignoring variables such as gender/sex in their analysis. (15)

Now, however, there is now a shift in research towards a female phenotype of ASD and more female children receive an autism diagnosis. Causes for diagnostic bias might be that male children on the autism spectrum show more obvious or easily identifiable repetitive patterns in behavior, interests, activities (RRBIs) than girls since the latter rather hyper-fixate on animals or dolls. (15) Also, females with ASD have better socio-emotional reciprocity (nonverbal communication, appropriate facial communication, offering comfort) and have a tendency to masking their autistic symptoms while still perceiving them more than men. (15)

The discovery of these differences in the female phenotype result in a shift of symptom structure and classification and why it motivates research on how biased the diagnosis through ADOS is. (16) Definitions in the DSM and ICD and clinical tools such as the ADOS have been based on Kanner and Asperger's descriptions and therefore their sensitivity has been fit to the male phenotype. (15)

Adamou et. al. (16) have tested the gender bias of the ADOS classification of patients into autistic vs. non-spectrum. The ADOS contains five modules each with a protocol of activities or social processes in which items are given scores from zero indicating "no abnormality of type specified" to three indicating "moderate to severe abnormality".

In their sample of people diagnosed with ASD based on the DSM-5, they found that the mean ADOS score for men with ASD diagnosis was 11.5, whereas women had a mean score of 6 - which is below the diagnostic threshold for ASD. For the people without ASD the mean for men was 5.7 and for women 4. They conclude that relying excessively on ADOS scores therefore may introduce gender bias against females and that the ADOS sensitivity is lower for autism in females. (16) Instead the thresholds for ADOS score indicating a ASD diagnosis should probably be adjusted for females - or the tested items and their rating adjusted to the female phenotype.

5.3 Analysis of Bias in ML model

Firstly, bias could be introduced in the OBC through unbalanced sampling since - similarly to other studies on autism - the female-male ratio of the studied cohort was unbalanced with 76.8 percent male patients, 18.5 percent female and 4.7 percent with unknown gender. It is, however, with the background on how autism research shifts towards differentiating symptoms of female and male children with ASD, relevant to test the OBC model on a more balanced dataset to see if this influences the performance of the model.

Furthermore, using the ADOS as a tool of comparison to assess the model might turn out to not be an optimal or appropriate measure due to the bias we have seen that the ADOS has.

Since the mean ADOS score for autistic as well as non-autistic females seems to have a high likelihood to be below the diagnostic cut-off, if the model returns similar results as ADOS, it is therefore also likely to wrongly categorize females as not on the autism spectrum. The authors don´t provide a general analysis how differently the model performs in classifying female compared to male children. One could compare how many false positives are male compared to female and how the correlation to ADOS scores differs between female and male participants. Also, analyzing false negatives for different gender groups would be relevant.

Additionally, for debiasing this application of ML it would be necessary to assess how girls are classified differently in each behavioral category. For example, there would be indication that with better non-verbal communication there scores for smile and showing might be better.

It also indicates that we should ask if it is advisable to create separate models for female and male patients due to the weights of different factors such as socio-emotional reciprocity being different.

6 Conclusion

We have seen that applying machine learning models without taking into consideration the existing socio-cognitive bias in psychological diagnosis and treatment processes could amplify these biases in

models and that there is still too little consideration of this risk in the field.

In the ML model by Barak-Corren et. al. gender bias was considered by training separate models for female and male, however, we argued that there are racial bias influences. We found overrepresentation of certain ethnicities in the case group, while also assessing potential for wrong risk scores through missing or incorrect diagnosis and medication.

In Duda´s et. al. model to diagnose autism gender bias must be taken into consideration and I stressed the necessity of adjusting diagnostic tools and ML models to account for the evolving understanding of ASD in females.

In both studies a more nuanced analysis of performance results for different subgroups is consequently advisable to improve model performance. Also, I suggested ways in which features for subgroups could differ and why therefore training different models might be useful.

We can conclude that future work on ML applications in psychiatry should be more aware of bias analysis, especially taking into account the existing research in psychology on how bias psychiatric concepts might be. Studies should take into account how datasets might have to split into subgroups either for training or to analyze afterwards if results of the model differ between these groups. Here it is important - as previous papers have noted - to compare the ratio of a model´s predictions by group and by the intersection of groups. For each group ratios should be the same or maintained from the ratios in reality and also performance should be equal to avoid social inequities. (3)

In the future, the spread of a more uniform standard and widely used bias detection or mitigation strategy would be advisable to avoid progress in the field benefiting only certain groups and instead leveraging the beneficial effect of machine learning for objectivity and inclusiveness in psychiatry.

References

[1] Ziad Obermeyer et al. 2019. "Dissecting racial bias in an algorithm used to manage the health of populations." Science366, 447-453.DOI:10.1126/science.aax2342

[2] Roberts, Steven O., Carmelle Bareket-Shavit, Forrest A. Dollins, Peter D. Goldie, and Elizabeth Mortenson. 2020. “Racial Inequality in Psychological Research: Trends of the Past and Recommendations for the Future.” Perspectives on Psychological Science 15 (6): 1295–1309. https://doi.org/10.1177/1745691620927709.

[3] Timmons, Adela C., Jacqueline B. Duong, Natalia Simo Fiallo, Theodore Lee, Huong Phuc Quynh Vo, Matthew W. Ahle, Jonathan S. Comer, LaPrincess C. Brewer, Stacy L. Frazier, and Theodora Chaspari. 2023. “A Call to Action on Assessing and Mitigating Bias in Artificial Intelligence Applications for Mental Health.” Perspectives on Psychological Science 18 (5): 1062–96. https://doi.org/10.1177/17456916221134490.

[4] Tay, Louis, Sang Eun Woo, Louis Hickman, Brandon M. Booth, and Sidney D’Mello. 2022. “A Conceptual Framework for Investigating and Mitigating Machine-Learning Measurement Bias (MLMB) in Psychological Assessment.” Advances in Methods and Practices in Psychological Science 5 (1): 25152459211061337. https://doi.org/10.1177/25152459211061337.

[5] Mosteiro, Pablo, Jesse Kuiper, Judith Masthoff, Floortje Scheepers, and Marco Spruit. 2022. “Bias Discovery in Machine Learning Models for Mental Health.” Information 13 (May): 237. https://doi.org/10.3390/info13050237.

[6] Barak-Corren, Yuval, Victor M. Castro, Solomon Javitt, Alison G. Hoffnagle, Yael Dai, Roy H. Perlis, Matthew K. Nock, Jordan W. Smoller, and Ben Y. Reis. 2017. “Predicting Suicidal Behavior From Longitudinal Electronic Health Records.” American Journal of Psychiatry 174 (2): 154–62. https://doi.org/10.1176/appi.ajp.2016.16010077.

[7] Garb, Howard N. 2021. “Race Bias and Gender Bias in the Diagnosis of Psychological Disorders.” Clinical Psychology Review 90 (December): 102087. https://doi.org/10.1016/j.cpr.2021.102087.

[8] Akinhanmi, Margaret O, Joanna M Biernacka, Stephen M Strakowski, Susan L McElroy, Joyce E Balls Berry, Kathleen R Merikangas, Shervin Assari, et al. 2018. “Racial Disparities in Bipolar Disorder Treatment and Research: A Call to Action.” Bipolar Disorders 20 (6): 506–14. https://doi.org/10.1111/bdi.12638.

[9] Anderson, Laura M., Lynda S. Lowry, and Karl L. Wuensch. 2015. “Racial Differences in Adolescents’ Answering Questions About Suicide.” Death Studies 39 (10): 600–604. https://doi.org/10.1080/07481187.2015.1047058.

[10] Bommersbach, Tanner J., Robert A. Rosenheck, and Taeho Greg Rhee. 2023. “Racial and Ethnic Differences in Suicidal Behavior and Mental Health Service Use among US Adults, 2009–2020.” Psychological Medicine 53 (12): 5592–5602. https://doi.org/10.1017/S003329172200280X.

[11] Ramchand, Rajeev, Joshua A. Gordon, and Jane L. Pearson. 2021. “Trends in Suicide Rates by Race and Ethnicity in the United States.” JAMA Network Open 4 (5): e2111563–e2111563. https://doi.org/10.1001/jamanetworkopen.2021.11563.

[12] Garlow, Steven J., David Purselle, and Michael Heninger. 2005. “Ethnic Differences in Patterns of Suicide Across the Life Cycle.” American Journal of Psychiatry 162 (2): 319–23. https://doi.org/10.1176/appi.ajp.162.2.319.

[13] Rockett, Ian RH, Shuhui Wang, Steven Stack, Diego De Leo, James L. Frost, Alan M. Ducatman, Rheeda L. Walker, and Nestor D. Kapusta. 2010. “Race/Ethnicity and Potential Suicide Misclassification: Window on a Minority Suicide Paradox?” BMC Psychiatry 10 (1): 35. https://doi.org/10.1186/1471-244X-10-35.

[14] Duda, M, J A Kosmicki, and D P Wall. 2014. “Testing the Accuracy of an Observation-Based Classifier for Rapid Detection of Autism Risk.” Translational Psychiatry 4 (8): e424–e424. https://doi.org/10.1038/tp.2014.65.

[15] Young, H., M.-J. Oreve, and M. Speranza. 2018. “Clinical Characteristics and Problems Diagnosing Autism Spectrum Disorder in Girls.” Archives de Pédiatrie 25 (6): 399–403. https://doi.org/10.1016/j.arcped.2018.06.008.

[16] Adamou, Marios, Maria Johnson, and Bronwen Alty. 2018. “Autism Diagnostic Observation Schedule (ADOS) Scores in Males and Females Diagnosed with Autism: A Naturalistic Study.” Advances in Autism 4 (2): 49–55. https://doi.org/10.1108/AIA-01-2018-0003.