MPDD-AVG: Multimodal Personality-Aware Depression Detection via Audio-Visual Interview and Gait Analysis

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Abstract

Depression is a prevalent mental health disorder affecting individuals across the lifespan, with significant impact on young adults and the elderly population. However, existing depression detection approaches predominantly rely on conversational or interview-based modalities with limited age diversity, while ambulatory behavioral signatures such as gait characteristics, though recognized as important clinical indicators of psychomotor symptoms, remain largely unexplored. Moreover, current methods establish direct data-to-score mappings without modeling individual differences, overlooking psychomotor domains and the inter-individual heterogeneity attributable to personality profiles, demographic variables, and comorbid conditions. To address these limitations, we introduce MPDD-AVG challenge, a comprehensive benchmark that uniquely integrates two acitivies of semi-structured interview behavioral data and gait monitoring from wearable sensors. **The challenge is an updated version of MPDD2025@ACM MM2025**, which comprises two age-specific datasets: MPDD-Young (110 young adults) investigating academic stress and social functioning, and MPDD-Elderly (110 older adults) examining late-life depression influenced by chronic conditions and living arrangements. Each dataset features three complementary tracks: (1) audio-visual interview with personality modeling (A-V+P), (2)

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integrated audio-visual-gait multimodal analysis (A-V-G+P) that fuses conversational cues with ambulatory patterns and personality information, and (3) gait-based detection with personality factors (G+P). Critically, we provide raw individual difference annotations including Big Five-10 personality dimensions, demographic variables, etc., rather than pre-engineered features only, explicitly encouraging participants to develop innovative personality-conditioned modeling strategies. We establish baseline multimodal fusion architectures and provide standardized evaluation protocols including depression severity regression and binary classification metrics. This challenge aims to advance the development of personalizedn depression detection systems that account for age-specific manifestations and inter-individual variability in depressive symptomatology.

Keywords

Automatic Depression Detection, Personality-aware, Multimodality, Gait.

1 Competition description

1.1 Background and Impact

Depression is a pervasive mental health disorder with a profound impact on global well-being, affecting millions and significantly hindering quality of life, productivity, and overall health [1]. The World Health Organization (WHO) categorizes depression as a leading cause of disability, underscoring its substantial societal and economic burden [2]. Timely detection and intervention are pivotal in mitigating the chronic and debilitating effects of depression. However, traditional methods, which primarily rely on self-reported questionnaires such as the PHQ-9 and BDI-II, are limited in their capacity to capture the dynamic and multifaceted nature of depressive symptoms. These methods are also susceptible to reporting biases and may not be sensitive to early or subtle changes in depressive states.

The advent of specialized datasets has been instrumental in advancing depression research by providing multimodal data that can enhance the detection and understanding of depressive symptoms. For instance, the AVEC challenge has contributed rich audiovisual interview data annotated with depression-related information, facilitating more nuanced assessments [3, 4, 5, 6, 7]. The DAIC-WoZ dataset has furthered our understanding by incorporating clinical interviews and PHQ-9 scores [8]. Other datasets, including the Pittsburgh dataset [9], the D-Vlog dataset [10], the EATD-Corpus [11], the CMDC [12], and the MODMA [13], have expanded the scope by integrating diverse data types like EEG and utilizing standard depression scales for evaluation. Additionally, datasets such as AMIGOS [14] and DEAP [15] have incorporated physiological data, offering insights into the physiological underpinnings of depression, while the SEED dataset provides EEG and eye movement data annotated with personality traits [16], highlighting the role of individual differences in depressive symptoms.

The challenge problem is of paramount importance and relevance to the multimedia research community, industry, and society over the next 3-5 years due to several compelling reasons. Firstly, the increasing prevalence of depression, particularly among young adults and the elderly population, necessitates the development of more sophisticated detection tools to address the growing demand for effective mental health interventions across the lifespan. Secondly, the integration of multimodal behavioral data—spanning conversational, affective, and ambulatory domains—and advanced analytics holds the potential to significantly improve the accuracy and reliability of depression assessments, leading to more timely and targeted interventions. Thirdly, as technology advances and the availability of digital health data and wearable sensors grows, there is a unique opportunity to leverage these resources to capture psychomotor symptoms and enhance our understanding of depression's multidimensional manifestations. Lastly, addressing this challenge is crucial for fostering advancements in personalized medicine, where interventions account for individual differences such as personality profiles and demographic characteristics, thereby improving treatment outcomes and reducing the overall burden of depression.

Table 1: Comparison of datasets for depression detection

Dataset	Audio-Visual	Gait	Depression	Personality	Gender	Age	Region	Disease
AVEC	✓	-	✓	-	✓	✓	-	-
DAIC-WoZ	✓	-	✓	-	✓	-	-	-
Pittsburgh	✓	-	✓	-	✓	✓	-	-
D-Vlog	✓	-	✓	-	✓	-	-	-
MMDA	✓	-	✓	-	✓	✓	-	-
EATD-Corpus	✓	-	✓	-	-	-	-	-
CMDC	✓	-	✓	-	✓	✓	-	-
MODMA	✓	-	✓	-	✓	✓	-	-
MPDD-AVG (ours)	✓	✓	✓	✓	✓	✓	✓	✓

1.2 Novelty

Despite the burgeoning interest in multimodal approaches for depression detection, existing datasets and methodologies exhibit notable limitations. Most existing approaches predominantly rely on conversational or interview-based modalities, while ambulatory behavioral signatures such as gait characteristics, though recognized as important clinical indicators of psychomotor symptoms, remain largely unexplored in computational frameworks. Moreover, many datasets establish direct correlations between behavioral signals and depression levels without modeling individual differences. This approach, while valuable, often fails to account for the nuanced individual variations in depressive symptoms influenced by personality traits, demographic factors, and health conditions [17, 18]. Furthermore, the demographic scope of existing datasets is predominantly confined to young adults, thereby overlooking other critical age groups, such as the elderly, who may present distinct patterns of depression manifestation.

To bridge these gaps, we introduce the **MPDD-AVG Challenge: Multimodal Personality-aware Depression Detection Using Audio-Visual Interview and Gait Analysis**, complemented by a novel benchmark dataset. This initiative uniquely integrates semi-structured interview behavioral data with continuous gait monitoring from wearable sensors, enabling holistic assessment spanning cognitive-linguistic, affective-paralinguistic, and psychomotor domains. The MPDD-AVG dataset incorporates audio, visual, and gait data from participants engaged in two complementary activities: semi-structured interviews and ambulatory monitoring. The dataset is enriched with annotations grounded in the PHQ-9 scale, the Big Five-10 personality dimensions, and comprehensive demographic and health condition information.

As compared to existing datasets, the MPDD-AVG dataset significantly enhances both the breadth of behavioral modalities and the depth of individual difference annotations, as underscored in Table 1. Critically, we provide raw personality trait annotations rather than pre-engineered features, explicitly encouraging participants to develop innovative personality-conditioned modeling strategies. By offering a more inclusive depiction of depression across age groups and a more granular representation of individual heterogeneity, the MPDD-AVG dataset is poised to facilitate the evolution of sophisticated multimodal models. These models are better equipped to navigate the complexities of mental health conditions, accounting for age-specific manifestations and inter-individual variability in depressive symptomatology.

The dataset's comprehensive annotation scheme and multimodal fusion framework are instrumental in advancing personalized depression detection. This capability is essential for fostering timely interventions and conducting precise assessments that consider the multifaceted nature of depression, thereby contributing to the broader objective of improved mental health management across diverse populations.

1.3 Tracks

The MPDD-AVG challenge comprises two age-specific datasets, each featuring three complementary sub-tracks that explore different combinations of behavioral modalities and personality modeling:

MPDD-Young: Young Adult Depression Detection focuses on 110 college students, investigating how academic stress, social environment, and personality traits contribute to depression in young adults. The dataset includes audiovisual recordings from semi-structured interviews, gait data from wearable sensors, Big Five-10 personality labels, and demographic information. This track features three sub-tracks: (1) Audio-Visual with Personality modeling (A-V+P), (2) Audio-Visual-Gait with Personality modeling (A-V-G+P) that integrates conversational cues with ambulatory patterns, and (3) Gait with Personality modeling (G+P).

MPDD-Elderly: Elderly Depression Detection examines depression in 110 older adults, exploring how chronic illnesses, living conditions, and personality traits influence late-life depression manifestation. The dataset includes audiovisual interviews, gait monitoring data, Big Five-10 personality labels, health condition annotations, and detailed demographic information. Similar to MPDD-Young, this track features three parallel subtracks: (1) A-V+P, (2) A-V-G+P, and (3) G+P, enabling comprehensive investigation of depression across cognitive-linguistic, affective-paralinguistic, and psychomotor behavioral domains in the elderly population.

1.4 Data Acquisition

1.4.1 MPDD-Elderly

The MPDD-Elderly dataset comprises data from 110 elderly participants, integrating audiovisual interview recordings and gait monitoring data to support multimodal depression assessment across cognitive-linguistic, affective-paralinguistic, and psychomotor behavioral domains.

Data Collection Protocol: Participants engaged in semi-structured interviews designed to elicit natural conversational behaviors and emotional responses. Following the interviews, participants were instructed to walk freely within a designated area while wearing inertial measurement unit (IMU) sensors that reflect gait characteristics such as walking speed, stride regularity, and postural dynamics.

Annotations: The dataset includes PHQ-9 Scale Scores for standardized depression assessment, Big Five-10 personality trait evaluations, comprehensive demographic information (age, gender, family situation, economic status), and disease labels accounting for health conditions related to the endocrine, circulatory, and nervous systems. This multifaceted annotation scheme enables nuanced understanding of how chronic illnesses, living conditions, and personality traits influence depression manifestation in older adults.

Task Structure: The dataset supports three classification tasks: (1) Binary classification (normal/depressed), (2) Ternary classification (normal/mildly depressed/severely depressed), and (3) Quinary classification (normal/mildly/moderate/moderately severe/severe).

1.4.2 MPDD-Young

The MPDD-Young dataset comprises data from 110 young adults, offering comprehensive multimodal data through audiovisual interviews and ambulatory gait monitoring.

Data Collection Protocol: Participants underwent semi-structured interviews designed to assess academic stress, social functioning, and emotional well-being. Subsequently, participants walked naturally within a designated area while equipped with wearable IMU sensors, capturing continuous gait data including temporal and spatial parameters that may reflect psychomotor symptoms of depression.

Annotations: The dataset includes PHQ-9 Scale Scores for depression severity assessment, Big Five-10 personality trait evaluations, and demographic information (gender, age, birth region). This comprehensive annotation enables analysis of how academic stress, social environment, and personality traits contribute to depression in young adults.

Task Structure: The dataset supports two classification tasks: (1) Binary classification (normal/depressed) and (2) Ternary classification (normal/mildly depressed/severely depressed).

1.5 Metrics

The Challenge employs comprehensive metrics to evaluate multimodal depression detection models across classification and regression tasks. These metrics assess model performance while accounting for class imbalance and clinical relevance.

1.5.1 Classification Metrics

Accuracy measures the proportion of correct predictions:

$$\text{Acc} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}} \tag{1}$$

F1 Score balances precision and recall, particularly crucial for imbalanced datasets common in mental health applications:

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2}$$

Where:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

Macro-F1 Score computes F1 scores independently for each class and averages them, ensuring equal weight to all depression severity levels regardless of sample size:

$$\text{Macro-}F_1 = \frac{1}{C} \sum_{i=1}^{C} F_1^{(i)} \tag{3}$$

where C is the number of classes.

Cohen's Kappa measures inter-rater agreement, accounting for chance agreement, which is particularly valuable for assessing clinical diagnostic consistency:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{4}$$

where p_o is the observed agreement and p_e is the expected agreement by chance.

1.5.2 Regression Metrics

For depression severity prediction tasks, we employ:

Root Mean Squared Error (RMSE) quantifies prediction error magnitude:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{5}$$

Mean Absolute Error (MAE) provides interpretable average prediction error:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{6}$$

Concordance Correlation Coefficient (CCC) assesses agreement between predicted and actual PHQ-9 scores, combining precision and accuracy:

$$\text{CCC} = \frac{2\rho\sigma_y\sigma_{\hat{y}}}{\sigma_y^2 + \sigma_{\hat{y}}^2 + (\mu_y - \mu_{\hat{y}})^2} \tag{7}$$

where ρ is Pearson's correlation coefficient, σ denotes standard deviation, and μ denotes mean.

1.5.3 Track-Level Evaluation

The final evaluation score for each track is calculated as the weighted average across all classification and regression tasks:

$$\text{Score}_{track} = \alpha \cdot \text{Macro-}F_1 + \beta \cdot \text{CCC} + \gamma \cdot \kappa \tag{8}$$

where α, β, and γ are weights that sum to 1, reflecting the relative importance of different aspects of model performance. This composite metric ensures comprehensive assessment across depression severity classification, continuous score prediction, and diagnostic consistency.

1.6 Baselines, Code, and Material Provided

In this challenge, we provide: (i) baseline code for all sub-tracks including A-V+P, A-V-G+P, and G+P (open source on GitHub[1]); (ii) a baseline paper describing the challenge background, dataset details, baseline systems, and results; (iii) the MPDD-AVG dataset conditioned on signed EULA agreements; (iv) standardized audio-visual and gait feature sets; and (v) raw individual difference annotations including Big Five-10 personality traits, demographics, and etc.

[1] https://github.com/hacilab/

1.7 Baseline System

The baseline model integrates audio-visual interview features with gait characteristics and personality information for depression detection. The architecture fuses multimodal behavioral data through transformer-based attention mechanisms to predict depression severity levels, supporting both classification and regression tasks across all sub-tracks. Implementation details and training scripts are available in the challenge repository.

2 Organizational aspects

2.1 Protocol

The Challenge is structured into several stages to ensure a comprehensive and fair evaluation process:

Stage 1: Call for Participation

The organizers will launch the challenge website and advertise the call for participation. This will be done through various channels including email lists, professional contacts, and social media to attract a wide range of participants.

Stage 2: Registration and Baseline Release

Participants are required to register their teams on the challenge website and sign the End User License Agreement (EULA). Following registration, the organizers will provide participants with access to the training and validation datasets and labels, along with related documents such as the challenge guidelines. Additionally, the baseline paper detailing the initial model performance and code will be released to assist participants in getting started.

Stage 3: Model Validation

Participants are encouraged to use the shared validation set to evaluate their models. However, to ensure fair competition, each team is restricted to a maximum of five submission attempts per sub-challenge for the test partition. The organizers will compare the submitted results with the ground truth. The ranking of the models will be based on predefined metrics such as Accuracy and F1 Score for both sub-challenges.

Stage 4: Paper Submission and Review

To be eligible for the final evaluation, each team must submit a paper detailing their proposed methodology and the achieved results. This paper should include thoroughly explained source code, well-trained models, and associated checkpoints. The submissions will undergo a rigorous peer-review process conducted by the challenge technical program committee. Only contributions that meet the terms and conditions will be eligible for consideration. The organizers will not participate actively but will re-evaluate the findings from the best-performing systems in each sub-challenge.

Stage 5: Challenge Organization

The final stage of the challenge will involve organizing the event at the ACM Multimedia Conference (MPDD 2026), where the results will be presented, and the winners will be announced.

2.2 Rules

The MPDD Challenge is designed with a clear set of rules to ensure fairness and reproducibility across all submissions. The rules are as follows:

Access to Data Participants will be granted access to the training and validation sets to develop their models. They are encouraged to make full use of utilize the audio and visual features provided within the dataset for model development purposes.

Use of Pre-trained Models Participants may freely use pre-trained weights obtained from open-source datasets or models to initialize their target models. This practice is allowed to facilitate faster development cycles and to encourage innovation in model architecture and algorithm design.

Restrictions on Data Usage To maintain the integrity of the challenge, participants are explicitly prohibited from using additional private or in-house datasets to pre-train their models. Compliance with this rule ensures that all participants are evaluated on an equal footing.

Submission Limitations Participants are restricted to a maximum of five submission attempts per day. Each submission will consist of the model's predictions on the test partition, along with the corresponding model and checkpoints/weights.

Evaluation Metrics The organizers will evaluate the submitted models using two predefined metrics: Accuracy and F1 Score. These metrics will be computed by comparing the participants' predictions against the ground-truth labels.

Final Ranking The final test results of each team will be used for the final ranking in the challenge. This ensures that the models are thoroughly tested and their performance is accurately assessed.

Reproducibility All materials, including data, must be accessible to all participating teams to ensure that the facial reaction models submitted by participants are fully reproducible.

Organizer's Role The organizers will not actively participate in the challenge but will undertake a re-evaluation of the findings from the best-performing systems in each sub-challenge to validate the results.

Eligibility The challenge is open to any researcher from any organization based anywhere in the world, fostering a global collaborative environment in addressing the complex issue of depression detection.

2.3 Timeline

The approximate timeline is proposed to be as follows:

- **05/3/2025:** Launching Challenge website and call for participation.
- **05/3/2025:** Registration open.
- **1/5/2025:** Baseline system, datasets and results submission website released.
- **15/06/2025:** Deadline for submitting results .
- **20/06/2025:** Result announced.
- **10/07/2025:** Paper submission deadline.
- **16/07/2025:** Paper acceptance notification.
- **6/08/2024:** Camera ready paper submission deadline.

2.4 Competition promotion

We are planning to promote the challenge via different social media challenges (e.g., X, and LinkedIn). In addition, we will advertise our challenge via mailing lists (e.g., robotics-worldwide, CVML list, chi-announcements ACM list, ICMI Multimodal announcements ACM list, comp.ai.neural-nets Google Groups, etc.). This challenge will promote openness of mind, ideas, and expression. Furthermore, regardless of age, sex, gender, gender identity and expression, sexual orientation, (dis)ability, physical appearance, race, ethnicity, nationality, marital status, military status, veteran status, religious beliefs, dietary requirements, childbirth and pregnancy-related medical conditions, or childcare requirements, we will provide a safe, respectful, and harassment-free challenge environment for everyone. When planning the challenge's schedule, we will respect and consider the implications of different time zones.

3 Resources

3.1 Organizing Team

The challenge organizing team comprises leading research groups from 6 Universitis spanning expertise in affective computing, human behavior analysis, multimodal machine learning, and human-robot interaction. The team collectively holds extensive experience in organizing workshops and challenges at premier conferences including ACM Multimedia, ICRA, and IROS.

3.2 Support and Facilities Requested

We propose a hybrid format to maximize global accessibility and inclusivity. We request conference facilities to host a hybrid workshop with: (i) presentation room equipped with video conferencing capabilities for remote participants; (ii) session space for in-person demonstrations; and (iii) technical support for live streaming and interactive Q&A sessions. This format enables participation from researchers worldwide regardless of geographical or financial constraints, fostering diverse perspectives in advancing personalized depression detection technologies.

References

[1] S. Moussavi, S. Chatterji, E. Verdes, A. Tandon, V. Patel, and B. Ustun, "Depression, chronic diseases, and decrements in health: results from the world health surveys," *The Lancet*, vol. 370, no. 9590, pp. 851–858, 2007.

[2] W. H. Organization *et al.*, "Depression and other common mental disorders: global health estimates," 2017.

[3] M. Valstar, B. Schuller, K. Smith, F. Eyben, B. Jiang, S. Bilakhia, S. Schnieder, R. Cowie, and M. Pantic, "Avec 2013: the continuous audio/visual emotion and depression recognition challenge," in *Proceedings of the 3rd ACM international workshop on Audio/visual emotion challenge*, 2013, pp. 3–10.

[4] M. Valstar, B. Schuller, K. Smith, T. Almaev, F. Eyben, J. Krajewski, R. Cowie, and M. Pantic, "Avec 2014: 3d dimensional affect and depression recognition challenge," in *Proceedings of the 4th international workshop on audio/visual emotion challenge*, 2014, pp. 3–10.

[5] M. Valstar, J. Gratch, B. Schuller, F. Ringeval, D. Lalanne, M. Torres Torres, S. Scherer, G. Stratou, R. Cowie, and M. Pantic, "Avec 2016: Depression, mood, and emotion recognition workshop and challenge," in *Proceedings of the 6th international workshop on audio/visual emotion challenge*, 2016, pp. 3–10.

[6] F. Ringeval, B. Schuller, M. Valstar, J. Gratch, R. Cowie, S. Scherer, S. Mozgai, N. Cummins, M. Schmitt, and M. Pantic, "Avec 2017: Real-life depression, and affect recognition workshop and challenge," in *Proceedings of the 7th annual workshop on audio/visual emotion challenge*, 2017, pp. 3–9.

[7] F. Ringeval, B. Schuller, M. Valstar, N. Cummins, R. Cowie, L. Tavabi, M. Schmitt, S. Alisamir, S. Amiriparian, E.-M. Messner *et al.*, "Avec 2019 workshop and challenge: state-of-mind, detecting depression with ai, and cross-cultural affect recognition," in *Proceedings of the 9th International on Audio/visual Emotion Challenge and Workshop*, 2019, pp. 3–12.

[8] J. Gratch, R. Artstein, G. M. Lucas, G. Stratou, S. Scherer, A. Nazarian, R. Wood, J. Boberg, D. DeVault, S. Marsella *et al.*, "The distress analysis interview corpus of human and computer interviews." in *LREC*. Reykjavik, 2014, pp. 3123–3128.

[9] H. Dibeklioğlu, Z. Hammal, and J. F. Cohn, "Dynamic multimodal measurement of depression severity using deep autoencoding," *IEEE journal of biomedical and health informatics*, vol. 22, no. 2, pp. 525–536, 2017.

[10] J. Yoon, C. Kang, S. Kim, and J. Han, "D-vlog: Multimodal vlog dataset for depression detection," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 36, no. 11, 2022, pp. 12 226–12 234.

[11] Y. Shen, H. Yang, and L. Lin, "Automatic depression detection: An emotional audio-textual corpus and a gru/bilstm-based model," in *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2022, pp. 6247–6251.

[12] B. Zou, J. Han, Y. Wang, R. Liu, S. Zhao, L. Feng, X. Lyu, and H. Ma, "Semi-structural interview-based chinese multimodal depression corpus towards automatic preliminary screening of depressive disorders," *IEEE Transactions on Affective Computing*, vol. 14, no. 4, pp. 2823–2838, 2022.

[13] H. Cai, Z. Yuan, Y. Gao, S. Sun, N. Li, F. Tian, H. Xiao, J. Li, Z. Yang, X. Li *et al.*, "A multi-modal open dataset for mental-disorder analysis," *Scientific Data*, vol. 9, no. 1, p. 178, 2022.

[14] J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras, "Amigos: A dataset for affect, personality and mood research on individuals and groups," *IEEE transactions on affective computing*, vol. 12, no. 2, pp. 479–493, 2018.

[15] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 18–31, 2011.

[16] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks," *IEEE Transactions on autonomous mental development*, vol. 7, no. 3, pp. 162–175, 2015.

[17] D. N. Klein, R. Kotov, and S. J. Bufferd, "Personality and depression: explanatory models and review of the evidence," *Annual review of clinical psychology*, vol. 7, no. 1, pp. 269–295, 2011.

[18] M.-T. Lo, D. A. Hinds, J. Y. Tung, C. Franz, C.-C. Fan, Y. Wang, O. B. Smeland, A. Schork, D. Holland, K. Kauppi *et al.*, "Genome-wide analyses for personality traits identify six genomic loci and show correlations with psychiatric disorders," *Nature genetics*, vol. 49, no. 1, pp. 152–156, 2017.