Identification of Treatment Resistant Major Depressive Disorder Using a Machine Learning Algorithm

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Background

- Major depressive disorder (MDD) is a serious mental health condition that may lead to reduced quality of life and poor health outcomes. Validated measures, such as the Patient Health Questionnaire-9 (PHQ-9),[1] are used to measure symptom severity over time.
- Many patients with major depressive disorder (MDD) suffer from treatment resistant depression (TRD), but there is no consensus on how to define and identify TRD in practice.[2]
- Existing definitions are challenging to implement in real-world datasets and lead to wide differences in estimated TRD prevalence, impeding research on TRD treatment patterns and outcomes.[3]
- Machine learning methods have demonstrated strong performance in identifying patients with specified characteristics at scale, but their potential to reliably identify TRD cases in real-world data is unexplored.

Objective

This study aimed to evaluate the performance of a machine learning algorithm in identifying physician-attested cases of TRD within a broader MDD population using structured real-world data.

Methods

Study Design

- Retrospective observational study conducted using data from the PremiOM™ MDD Dataset, a large, de-identified multi-source real-world data network with claims and specialty EMR data on adult patients with MDD in the United States.

Eligibility Criteria

- Within this dataset, unstructured clinical notes from psychiatrists were examined for the presence of documented TRD and used to create the TRD-positive cohort (**Figure 1**).
- A TRD-negative group was sampled among MDD patients with no TRD attestation, at a ratio of 4:1.

Figure 1. Example of Clinician Attestation of TRD in Clinical Note Text

Continue Xanax 0.5 mg PO PRN Qhs for anxiety/insomnia. [CR][LF](uses sparingly) [CR][LF][CR][LF]4. Continue Abilify to 7.5mg PO QHS for treatment resistant depression symptoms and irritability/agitation

Methods (cont.)

Analysis

- The study dataset was divided into training (80%), testing (10%), and validation (10%) sets.
- A machine learning-based classification tool (Patient Finder™, part of OM1's PhenOM™ digital phenotyping platform) was calibrated using the training set to distinguish labeled TRD cases using structured health history data (e.g., coded diagnoses, procedures, lab tests, medication history, and demographic factors) from within one year prior to the prediction index date. Classification performance was evaluated using the validation set.
- Depression symptom severity for patients with TRD and patients without TRD was assessed using the PHQ-9.

Results

- The TRD-positive cohort included 3,771 patients who met the TRD attestation criteria.
- The TRD-negative cohort included 15,084 MDD patients with no TRD attestation.
- The machine learning model performed well in identifying TRD-positive cases, with an area under the receiver operating characteristic (AUC) of 0.87 in the validation set (**Figure 2**).
- Performance remained strong when evaluating only men (33.1% of study dataset, AUROC: 0.88); only women (66.9%, AUROC: 0.87); and within selected age bands (**Table 1**).
- Patients with more severe depression symptoms, as measured by the PHQ-9, were more likely to be identified as TRD-positive cases (**Figure 3**).
- Performance was driven by a range of factors including indications of MDD severity, patterns of prior mental health treatment, and evidence of hormone imbalance.

Conclusions

- A machine learning model trained using a physician attestation to identify a clinically meaningful TRD cohort successfully identified positive TRD cases using only structured medical record data.
- The performance of the model demonstrates that a machine learning tool can identify TRD patients similar to those considered TRD-positive by clinician attestation as a sources of truth in defining TRD.
- Future research should focus on further validation of this approach and its utility in creating TRD patient cohorts relative to other methods of identifying TRD patients.

Figure 2. Area Under the Receiver Operating Characteristic Curve (AUC)

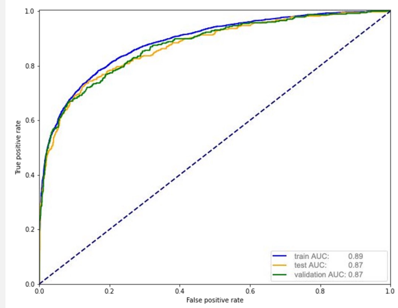

Figure 2. Observed PHQ-9 Scores Among Patients with and without TRD

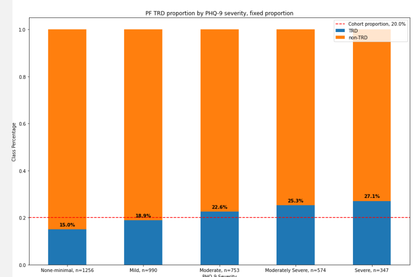

Table 1. Machine Learning Model Performance in Patient Subgroups

Cohort	% of Total Cohort	TRD-Positive Rate	One-Year AUC
All	100%	20%	0.87
Male	33.1%	22.8%	0.88
Female	66.9%	18.6%	0.87
Age ≥ 30	72.6%	23.0%	0.87
Age < 30	27.4%	11.8%	0.87
Age ≥ 50	34.9%	26.4%	0.84
Age < 50	65.1%	16.6%	0.88
Age ≥ 65	10.9%	26.7%	0.83
Age < 65	89.1%	19.1%	0.88
White	35.6%	20.8%	0.86
'Non-white'	4.2%	19.0%	0.85

Conference

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References

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