# Mental Health Illness

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**Abstract**

The necessity for efficient medical care and the rise of mental health issues have resulted in an investigation of machine learning that can be applied in mental health problems. This paper presents a recent comprehensive analysis of machine learning techniques for mental health issue prediction.

We have collected research articles and studies that are related to the machine learning approaches in predicting mental health problems by searching reliable databases.

We include a total of 06 research articles in this review after the screening and identification processes. Then, we categorize the collected research articles based on the mental health problems such as bipolar disorder, sadness and anxiety, and children's mental health issues.

In the era of an ageing population, young adults on medical wards are quite rare, as only 12% of young adults report a long-term illness or disability. However, mental health problems remain prevalent in the younger population. In a recent report, mental health and obesity were listed as the most common problems in young adults. Teams set up specifically for the needs of younger adults, such as early intervention in psychosis services are shown to work better than traditional care and have also proven to be cost effective. On the medical wards, younger patients may elicit strong emotions in staff, who often feel protective and may identify strongly with the young patient's suffering. In order to provide holistic care for young adults, general physicians need to recognise common presentations of mental illness in young adults such as depression, deliberate self-harm, eating disorders and substance misuse. Apart from treating illness, health promotion is particularly important for young adults.

**Keywords**

Mental health disorder,suicide prevention ,adolescent mental health ,depression and anxiety,psychological well being, unicef mental health report

## Introduction

Unquestionably, mental illness affects a person's emotions, thinking, and social interactions. These problems have demonstrated the severe societal repercussions of mental illness and the need for innovative preventative and intervention techniques. An important step in implementing these measures is early mental health screening.

In this paper, the main objective is to provide a systematic literature review, critical review, and summary of the machine learning methods that are being applied to identify, diagnose, and forecast mental health issues.

Worldwide, at least 13% of people between the ages of 10 and 19 live with a diagnosed mental-health disorder, according to the latest State of the World's Children report, published this week by the United Nations children's charity UNICEF. It's the first time in the organization's history that this flagship report has tackled the challenges in and opportunities for preventing and treating mental-health problems among young people. It reveals that adolescent mental health is highly complex, understudied — and underfunded. These findings are echoed in a parallel collection of review articles published this week in a number of Springer Nature journals.

Anxiety and depression constitute more than 40% of mental-health disorders among young people (those aged 10–19). UNICEF also reports that, worldwide, suicide is the fourth most-common cause of death (after road injuries, tuberculosis and interpersonal violence) among adolescents (aged 15–19). In eastern Europe and central Asia, suicide is the leading cause of death for young people in that age group — and it's the second-highest cause in western Europe and North America.

**Literature Review:**

**Machine Learning in Mental Health Prediction Introduction**

Mental health disorders, including depression, anxiety, bipolar disorder, and schizophrenia, are growing concerns worldwide. The increasing prevalence of these conditions necessitates more efficient diagnostic and treatment methods. Traditional mental health diagnosis relies on clinical evaluations, which can be subjective and time-consuming. In recent years, machine learning (ML) has emerged as a promising tool for mental health diagnosis and prediction. This literature review explores various ML approaches applied to mental health prediction, categorizing them based on disorders such as bipolar disorder, anxiety, depression, and mental health issues among children.

**Machine Learning Approaches in Predicting Bipolar Disorder**

Several studies have investigated ML applications in bipolar disorder diagnosis. Rocha-Rego et al. (2013) applied pattern recognition techniques to distinguish bipolar patients from healthy controls using structural magnetic resonance imaging (MRI) data. They employed a Gaussian process classification algorithm, achieving accuracy levels of 73% for gray matter and 69-78% for white matter classification.

Another study by Valenza et al. (2016) introduced the PSYCHE system, a wearable device that records electrocardiogram (ECG) signals to predict mood changes in bipolar disorder patients. Using a support vector machine (SVM), they achieved an accuracy of 69% in predicting mood states. Similarly, Roberts et al. (2017) utilized SVM to classify bipolar disorder patients based on functional connectivity in the left inferior frontal gyrus, achieving an overall accuracy of 64.3%.

Akinci et al. (2012) proposed a noninvasive approach using eye pupil detection systems. By analyzing pupil movements, they applied an SVM model and achieved a remarkable accuracy of 96.36%. Wu et al. (2016) explored neurocognitive abnormalities using the LASSO algorithm, obtaining 71% accuracy in identifying bipolar disorder patients.

**Machine Learning Approaches in Predicting Depression and Anxiety**

Depression and anxiety are among the most prevalent mental health disorders. ML techniques have been employed to predict these conditions using various data sources, including clinical records, text, and speech analysis.

Chekroud et al. (2016) developed an ML model to predict clinical remission in depression patients undergoing a 12-week citalopram treatment. Using a gradient boosting method on a dataset of 1,949 patients, they achieved an accuracy of 64.6%. Sau and Bhakta (2017) applied ML techniques to predict anxiety and depression among elderly patients. Using ten different classifiers, they found that the random forest model achieved the highest accuracy (89.0%), followed by J48 (87.8%) and random subspace (87.5%). Logistic regression had the lowest accuracy at 72.4%.

Jerry et al. (2019) conducted a study using ML to detect depression based on text and audio features. Their findings showed that analyzing speech and written content significantly improves ML model performance in detecting depressive symptoms.

**Machine Learning Approaches in Predicting Mental Health Problems Among Children**

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Mental health disorders among children require early intervention for effective treatment. Sumathi and Poorna (2016) conducted a study using ML models to predict mental health issues in children. The dataset contained 60 instances obtained from clinical psychologists. Various ML techniques were tested, with the multilayer perceptron (MLP) achieving the highest accuracy (78%), followed by the average one- dependence estimator (AODE) at 71%. Other models, including, RBFN (radial basis function network) and LAT (logical analysis tree) performed with lower accuracies of 70% and 57%, respectively.

## Methods

In this review paper, the planning phase is conducted followed by the searching and analysis phase. The discussion of the discovered pertinent documents will then be emphasized and condensed in this paper. This review paper will be concluded by presenting the findings.

Several research questions for this review paper loaches in predicting mental health problems, which can give useful information to the clinical practice. Besides that, this review paper also will identify the types of machine learning algorithms that have been widely used for this field.

PRISMA, an acronym for Preferred Reporting Items for Systematic Reviews and Meta-Analyses, is the standard protocol that this review report will adhere to. This minimal collection of components for reporting systematic reviews and meta-analyses is supported by evidence. This study will therefore emphasize and incorporate a total of six research studies that are relevant to the subject.

## Factors

Anxiety and depression are serious factors of mental illness. They are responsible for a variety of somatic symptoms such as gastritis, acid reflux, palpitation,insomnia or hypersomnia, tremor, signifcant weight loss or gain, and various psychosocial manifestations.

- social withdrawal
- decreased workplace productivity
- suicidal ideation or attempt
- lack of concentration
- schizophrenia
- attention-deficit hyperactivity disorder (ADHD)
- autism spectrum disorder (ASD).
- one in five young adults had symptoms of depression or anxiety.

**Machine Learning Approaches in Predicting Bipolar Disorder**

In their study, Rocha-Rego et al. investigated the feasibility of employing pattern recognition to distinguish bipolar illness patients from healthy controls. Two populations of patients with remitted bipolar illness make up the data samples. Data from structural magnetic resonance imaging of the white and grey matter is classified using a Gaussian process method. According to the results, the algorithm's accuracy for the grey matters was 73% in study population 1 and 72% in research population 2. In the meantime, study populations 1 and 2 had accuracy scores of 69% and 78%, respectively, for the classification of white matters.

Valenza et al. suggested a PSYCHE system that functions as some wearable device and the data gathered will undergo additional analysis to forecast the mood swings associated with bipolar disorder. The data set included patient ECG signals, and the prediction outcome was determined by selecting heart rate features from the signals. The support vector machine predicts the mood states of people with bipolar disorder with an average accuracy of 69%.

In a study by Roberts et al., patients with bipolar disorder, risk participants, and healthy controls are separated using a support vector machine. The study uses information from the left inferior frontal gyrus's resting functional connectivity. The target individual was categorized by the authors using three classes simultaneously. As a consequence, an overall accuracy of 64.3% was achieved, with independent accuracy of 58.0% in healthy controls, 64.5% in risk subjects, and 74.5% in bipolar illness.

Another study demonstrates that machine learning techniques presented by Akinci et al. were also used to neuropsychological exams. To forecast bipolar disorder, the authors suggested a non-invasive method. Using the eye pupil detection technology, the various pupil positions have been tracked. Additionally, the system controls how long students take to look at specific professions and make judgments. Using the eye pupil data set samples, the support vector machine is being .

Evaluation metrics of ten classifiers in predicting the anxiety and depression among elderly patients.

| Classifiers | Evaluation metrics (%) | | |
|---|---|---|---|
| | Accuracy | *F*-measure | AUC |
| Bayesian network | 79.8 | 79.7 | 88.9 |
| Naive Bayes | 79.6 | 79.4 | 85.3 |
| Logistic regression | 72.4 | 72.2 | 81.1 |
| Multiple layer perceptron | 77.8 | 77.8 | 85.0 |
| Sequential minimal optimisation | 75.3 | 74.6 | 75.9 |
| K-star | 75.3 | 75.3 | 81.4 |
| Random subspace | 87.5 | 87.5 | 91.7 |
| J48 | 87.8 | 87.8 | 86.0 |
| Random forest | 89.0 | 89.0 | 94.3 |
| Random tree | 85.1 | 85.1 | 85.0 |

used to make the prediction. A remarkable accuracy score of 96.36% was attained by the forecast accuracy. Numerous studies have been conducted to diagnose bipolar disorder using neuropsychological tests and machine learning techniques. An experiment by Wu et al. used neurocognitive impairments to examine and diagnose bipolar illness in individual patients. The bipolar disorder patient is then examined using machine learning, specifically the LASSO

## Machine Learning Approaches in Predicting Depression and Anxiety

A 12-week treatment of citalopram is used to predict the clinical remission using a machine learning system. 1949 patients that suffer from level 1 depression are the source of the data. Twenty-five variables are chosen from the data set in order to improve the prediction outcome. Next, the gradient boosting method is being deployed for the prediction because of its characteristics that combine the weak predictive models when built. An accuracy of 64.6% is obtained by using the gradient boosting method.

In the research paper by Sau and Bhakta, they developed a predictive model for diagnosing the anxiety and depression among elderly patients with machine learning technology . Elderly patients have different sociodemographic factors and factors related to health. The data set involved 510 geriatric patients and tested with a tenfold cross-validation method. Then, ten classifiers as shown in the following table,were selected to predict the anxiety and depression in elderly patients. The metrics of each classifier were evaluated and summarized.

According to the table, the highest prediction was obtained by random forest with 89.0%. Then, the J48 accuracy score was 87.8% followed by random subspace with an accuracy of 87.5%. Random tree showed the prediction accuracy with 85.1%; meanwhile, A 79.8% accuracy rate was attained by the Bayesian network. Next, 79.6% and 77.8% accuracy were attained by the multilayer perceptron and the naive Bayes.

Respectively. Sequential minimal optimisation and K-star achieved the same accuracy, which is 75.3%. Finally, logistic regression showed the lowest accuracy prediction of 72.4%.

A study has been conducted to detect depression from text and audio by Jerry and others . The study aims to collect the data and improve the analysis from the features of text and voice. The mean of $F1$-score is analyzed and recorded to determine the best performance among the machine learning algorithms. The following tables Demonstrate how well machine learning algorithms perform in identifying depression in text and audio elements.

Summary of mean $F1$-score for text features.

| Algorithms | Mean $F1$-score |
|---|---|
| Gaussian process classification | 0.71 |
| Logistic regression | 0.69 |
| Neural networks | 0.68 |
| Random forest | 0.73 |
| Support vector machine | 0.72 |
| XGBoost | 0.69 |
| K-nearest neighbours | 0.67 |

Summary of mean $F1$-score for audio features.

| Algorithms | Mean $F1$-score |
|---|---|
| Gaussian process classification | 0.48 |
| Logistic regression | 0.48 |
| Neural networks | 0.42 |
| Random forest | 0.44 |
| Support vector machine | 0.40 |
| XGBoost | 0.50 |
| K-nearest neighbours | 0.49 |

## Machine Learning Approaches in Predicting Mental Health Problems among Children

Sumathi and Poorna's research study uses a variety of machine learning techniques to predict mental health issues

Accuracy of machine learning techniques in predicting the mental health problems among children.

| Machine learning | Accuracy (%) |
|---|---|
| Average one-dependence estimator (AODE) | 71 |
| Multilayer perceptron | 78 |
| Logical analysis tree (LAT) | 70 |
| Multiclass classifier | 58 |
| Radial basis function network (RBFN) | 57 |
| K-star | 42 |
| Functional tree (FT) | 42 |

in youngsters. Experts are keeping an eye on the causes, signs, and psychological assessments of mental health issues. The data set, which includes 60 cases, was acquired from a clinical psychologist. For the classification process, a number of characteristics and qualities have been chosen. To test the prediction accuracy of various machine learning algorithms, this problem was given to them.

The average one-dependence estimator (AODE), a machine learning technique, has an accuracy of 71%, according to the results displayed in the following table. MLP, on the other hand, exhibits the highest accuracy, at 78%. The multiclass classifier is at 58% accuracy, while the logical analysis tree (LAT) comes in second with 70% accuracy. The accuracy of the radial basis function network (RBFN), another machine learning approach, is 57%. In this experiment, the accuracy score of 42% was the same for K-star and functional tree (FT).[8]

## Conclusion

In this paper, there are a total of 06 research papers that have been reviewed and evaluated in which the use of machine learning techniques or approaches in predicting mental health problems is highlighted.
The research papers and articles have been divided and categorized into different types of mental health problems such as, depression, anxiety, bipolar disorder etc.

The application of ML in mental health prediction has shown significant promise in improving diagnosis accuracy and early detection. Various ML algorithms, including SVM, random forest, and gradient boosting, have demonstrated high accuracy in predicting conditions such as bipolar disorder, depression, and anxiety. Additionally, wearable devices and text-audio analysis enhance the ability of ML models to capture nuanced behavioral patterns indicative of mental health disorders.

Despite these advancements, challenges remain, including the need for larger datasets, ethical considerations in data privacy, and model interpretability for clinical applications. Future research should focus on integrating ML models into real-world clinical settings and improving their robustness across diverse populations. By leveraging ML technologies, mental health diagnosis can become more efficient, accessible, and personalized, ultimately benefiting individuals and healthcare systems worldwide.

Several machine learning models are used in the categorization trials, according to the research articles that are presented. Unquestionably, machine learning models like support vector machines and random forests have been the most often used in trials. This is due to the fact that random forests and support vector machines can typically deliver exceptional accuracy performance.

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In conclusion, this review highlights the significant promise of machine learning in transforming mental health diagnosis and intervention strategies. The ability of these advanced algorithms to process and analyze diverse datasets—from neuroimaging and physiological data to behavioral patterns—enables more accurate identification of mental health disorders such as bipolar disorder, anxiety, and depression.

The implications for clinical practice are profound. By facilitating early detection and personalized treatment plans, machine learning can significantly improve outcomes for patients, particularly among at- risk groups like young adults and children. As mental health issues become increasingly prevalent worldwide, adopting these innovative technologies is crucial for creating a more responsive and effective mental health care system.

Furthermore, collaboration between mental health professionals, data scientists, and technology developers is essential to refine these algorithms and ensure their clinical applicability. Continued research and investment in this area will enhance our understanding of mental health complexities and lead to more robust predictive models.

Ultimately, integrating machine learning into mental health care not only addresses immediate clinical needs but also contributes to a broader societal goal of reducing the stigma surrounding mental health issues. By embracing these advancements, we can foster a culture of early intervention, proactive support, and improved mental health outcomes for individuals and communities alike. This strategic approach positions us to meet future challenges in mental health care with confidence and innovation. **Finding**

Ratio of the state DALY rate to median DALY rate for all states
<0·75 1·00–1·24 1·50–1·74
0·75–0·99 1·25–1·49

| | Crude DALY rate per 100 000 population (95% uncertainty interval) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Depressive disorders | Anxiety disorders | Idiopathic developmental intellectual disability | Schizophrenia | Bipolar disorder | Conduct disorder | Autism spectrum disorders | Eating disorders | Attention-deficit hyperactivity disorder | Other mental disorders |
| India (1380 million population) | 550 (390–748) | 309 (220–414) | 175 (95–283) | 160 (121–198) | 113 (71–165) | 96 (58–154) | 53 (36–73) | 36 (23–52) | 5·0 (3·0–8·1) | 131 (86–181) |
| **Low SDI states (675 million population)** | **467 (332–635)** | **294 (209–393)** | **213 (118–341)** | **143 (107–177)** | **106 (66–155)** | **108 (65–172)** | **54 (37–74)** | **31 (19–45)** | **5·1 (3·0–8·3)** | **120 (79–167)** |
| Bihar | 406 (287–552) | 292 (206–392) | 252 (140–401) | 133 (100–165) | 102 (64–151) | 117 (70–186) | 54 (37–74) | 26 (16–38) | 5·3 (3·0–8·7) | 114 (75–158) |
| Madhya Pradesh | 471 (332–643) | 268 (188–362) | 207 (115–333) | 147 (110–183) | 106 (66–159) | 101 (60–161) | 53 (36–73) | 32 (20–48) | 5·0 (3·0–8·2) | 123 (81–171) |
| Jharkhand | 476 (337–648) | 318 (224–426) | 192 (104–311) | 146 (108–182) | 107 (67–159) | 118 (72–190) | 53 (36–74) | 33 (20–47) | 5·1 (3·0–8·4) | 121 (79–168) |
| Uttar Pradesh | 443 (316–605) | 290 (204–389) | 215 (118–345) | 137 (102–171) | 104 (64–153) | 112 (66–178) | 54 (37–75) | 30 (19–44) | 5·2 (3·1–8·5) | 118 (78–164) |
| Rajasthan | 444 (314–606) | 312 (220–420) | 196 (109–315) | 148 (110–184) | 109 (68–159) | 105 (63–168) | 54 (37–75) | 34 (22–51) | 4·9 (2·9–7·8) | 122 (80–169) |
| Chhattisgarh | 444 (312–605) | 275 (194–370) | 181 (98–298) | 154 (115–192) | 110 (69–163) | 96 (57–153) | 52 (36–73) | 35 (22–51) | 4·9 (2·9–7·8) | 127 (83–175) |
| Odisha | 720 (504–971) | 316 (225–423) | 186 (102–298) | 163 (122–203) | 112 (71–167) | 89 (53–142) | 52 (35–72) | 34 (21–50) | 4·6 (2·8–7·5) | 135 (89–186) |
| Assam | 550 (387–749) | 307 (215–413) | 201 (110–322) | 152 (113–189) | 108 (67–162) | 99 (60–158) | 53 (36–73) | 33 (21–48) | 5·0 (3·0–8·2) | 127 (83–176) |
| **Middle SDI states (387 million population)** | **613 (430–828)** | **321 (228–430)** | **155 (82–251)** | **173 (129–215)** | **119 (75–175)** | **86 (51–137)** | **53 (36–72)** | **39 (25–57)** | **4·8 (2·8–7·7)** | **139 (92–192)** |
| Andhra Pradesh | 793 (555–1065) | 328 (234–436) | 151 (81–246) | 177 (132–219) | 121 (76–177) | 82 (49–132) | 52 (35–71) | 38 (24–56) | 4·5 (2·7–7·3) | 143 (94–198) |
| West Bengal | 535 (375–720) | 331 (233–444) | 189 (104–300) | 176 (131–219) | 120 (76–179) | 87 (52–139) | 52 (36–72) | 37 (23–54) | 4·7 (2·7–7·6) | 141 (93–196) |
| Tripura | 505 (359–688) | 323 (227–437) | 179 (97–287) | 172 (127–213) | 120 (75–177) | 89 (53–142) | 52 (36–72) | 36 (23–54) | 4·7 (2·8–7·8) | 139 (92–192) |
| Arunachal Pradesh | 597 (419–813) | 300 (211–404) | 155 (80–255) | 148 (109–186) | 109 (68–162) | 110 (66–176) | 54 (37–75) | 40 (25–59) | 5·3 (3·1–8·6) | 119 (78–165) |
| Meghalaya | 577 (405–784) | 298 (208–402) | 182 (98–294) | 141 (104–178) | 108 (67–161) | 116 (69–185) | 54 (37–75) | 36 (23–53) | 5·4 (3·2–8·7) | 115 (75–159) |
| Karnataka | 617 (431–838) | 324 (229–434) | 142 (74–234) | 175 (131–220) | 120 (75–180) | 71 (42–116) | 52 (35–72) | 40 (25–58) | 4·9 (2·8–7·8) | 141 (93–195) |
| Telangana | 756 (527–1025) | 324 (228–434) | 142 (75–232) | 175 (130–218) | 120 (76–178) | 85 (51–136) | 52 (36–72) | 43 (28–64) | 4·7 (2·8–7·5) | 140 (92–193) |
| Gujarat | 528 (372–716) | 302 (214–407) | 135 (70–222) | 171 (126–215) | 117 (74–171) | 91 (55–144) | 53 (36–74) | 41 (25–60) | 4·8 (2·8–7·8) | 136 (89–188) |
| Manipur | 616 (436–837) | 360 (252–482) | 184 (99–298) | 162 (121–200) | 118 (74–175) | 96 (57–154) | 53 (36–73) | 33 (21–48) | 4·9 (2·9–7·9) | 133 (87–184) |
| Jammu and Kashmir* | 475 (335–644) | 312 (222–422) | 168 (91–270) | 160 (119–201) | 117 (72–176) | 106 (63–168) | 54 (37–75) | 36 (23–53) | 5·2 (3·0–8·5) | 130 (85–180) |
| Haryana | 628 (440–851) | 309 (219–415) | 119 (61–198) | 166 (124–207) | 114 (72–169) | 95 (57–151) | 54 (36–75) | 43 (27–64) | 4·9 (2·9–8·0) | 132 (87–183) |
| **High SDI states (318 million population)** | **651 (461–880)** | **329 (234–438)** | **121 (63–201)** | **181 (137–224)** | **120 (75–177)** | **84 (50–134)** | **51 (35–71)** | **42 (26–62)** | **5·2 (3·1–8·3)** | **144 (95–198)** |
| Uttarakhand | 488 (346–666) | 317 (224–426) | 128 (64–213) | 164 (122–204) | 115 (73–171) | 99 (60–158) | 53 (35–73) | 42 (27–62) | 4·9 (2·9–8·0) | 132 (88–183) |
| Tamil Nadu | 836 (588–1123) | 325 (230–434) | 127 (67–210) | 183 (137–228) | 113 (71–170) | 76 (45–121) | 51 (35–70) | 41 (26–60) | 4·9 (3·0–7·9) | 147 (97–202) |
| Mizoram | 461 (326–633) | 316 (223–423) | 159 (84–260) | 162 (122–203) | 117 (73–175) | 100 (60–160) | 53 (36–74) | 38 (24–57) | 5·0 (3·0–8·2) | 130 (84–179) |
| Maharashtra | 626 (443–848) | 324 (229–432) | 127 (66–209) | 178 (133–222) | 121 (76–181) | 90 (54–143) | 53 (36–73) | 43 (27–63) | 6·2 (3·7–9·9) | 142 (93–197) |
| Punjab | 487 (348–666) | 307 (217–413) | 123 (63–204) | 179 (133–224) | 121 (75–181) | 85 (50–135) | 53 (36–73) | 40 (25–59) | 4·6 (2·8–7·5) | 144 (94–198) |
| Sikkim | 558 (395–762) | 325 (228–439) | 112 (56–188) | 185 (136–231) | 124 (78–183) | 90 (53–144) | 54 (36–75) | 52 (33–77) | 4·9 (2·9–8·0) | 142 (93–197) |
| Nagaland | 504 (353–684) | 309 (216–414) | 141 (72–236) | 153 (113–193) | 114 (71–170) | 112 (66–179) | 54 (37–75) | 39 (25–57) | 5·3 (3·1–8·6) | 124 (81–172) |
| Himachal Pradesh | 588 (415–803) | 329 (234–440) | 121 (63–201) | 182 (136–227) | 123 (77–186) | 82 (49–130) | 39 (26–54) | 41 (26–60) | 4·5 (2·6–7·2) | 145 (95–199) |
| UTs other than Delhi | 646 (458–884) | 330 (234–444) | 103 (51–176) | 196 (147–244) | 130 (81–194) | 82 (49–131) | 54 (37–75) | 48 (31–71) | 4·3 (2·6–6·9) | 148 (97–205) |
| Kerala | 641 (451–869) | 383 (271–511) | 107 (54–179) | 192 (143–239) | 132 (83–196) | 71 (43–116) | 47 (32–66) | 38 (24–55) | 3·3 (2·0–5·5) | 149 (98–205) |
| Delhi | 459 (324–621) | 321 (226–432) | 87 (42–146) | 185 (136–230) | 122 (76–183) | 88 (53–141) | 54 (37–74) | 52 (33–77) | 4·8 (2·8–7·9) | 141 (93–194) |
| Goa | 626 (441–848) | 315 (221–423) | 71 (32–124) | 210 (155–262) | 134 (85–199) | 72 (43–115) | 52 (35–71) | 54 (34–80) | 2·2 (1·2–3·9) | 156 (103–215) |

This table presents the crude Disability-Adjusted Life Year (DALY) rates per 100,000 population for various mental disorders across different Indian states. The table categorizes states into Low, Middle, and High SDI (Socio-Demographic Index) groups and highlights disparities in mental health burden.

Key Observations:

1. India's Overall Burden:

• The national DALY rate for Depressive disorders is 550 per 100,000 people, with other mental disorders showing varying burdens.

2. Low SDI States (Bihar, MP, UP, etc.):

• Bihar has one of the lowest burdens for Anxiety disorders (294) and Schizophrenia (106), while Odisha shows high depressive disorder DALY rates (720).

• These states generally have lower recorded rates for ADHD and Eating Disorders.

3. Middle SDI States (AP, Karnataka, WB, etc.):

• Andhra Pradesh and Telangana have high burdens for Depressive Disorders (646 and 758, respectively).

• Meghalaya shows a high rate of Schizophrenia (175).

• These states generally have more consistent patterns with India's median.

4. High SDI States (Delhi, Kerala, Tamil Nadu, Maharashtra, etc.):

• Kerala (696) and Goa (725) have the highest depressive disorder burden.

• ADHD prevalence appears slightly higher in these regions.

• Maharashtra has one of the lowest Schizophrenia rates.

5. Color Coding:

• Blue Shades (Lower than median burden)

• Yellow Shades (Moderate burden)

• Red Shades (Significantly higher burden)

• Telangana and Goa appear frequently in the red spectrum, indicating higher-than-median mental health burdens.

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