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Mental Health Consequences Of Covid-19 For Medical Students: Global Trends And Predictive Models

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Abstract: The COVID-19 pandemic has significantly impacted the mental health of medical students worldwide. This study examines anxiety and depression prevalence among students in India, Pakistan, China, and Bangladesh, integrating statistical analysis with machine and deep-learning models. Data from structured surveys revealed that 62.7% experienced anxiety, 54.2% depression, and 48.5% stress, with higher distress among female and hostel-residing students. Comparative analysis showed greater psychological burden in Pakistan and Bangladesh than in China and India. Among predictive techniques, the Hybrid LSTM-CNN achieved the best accuracy (91.2%, F1 = 0.89, AUC = 0.94), outperforming CNN, Random Forest, and Logistic Regression. Findings indicate that prolonged online learning, isolation, and academic pressure heightened distress during the pandemic. The proposed AI-based predictive framework can help institutions identify at-risk students and develop targeted mental-health interventions for future resilience.

***Index Terms* -** Mental health, COVID-19 pandemic, Predictive modelling, Global trends

I. INTRODUCTION

The COVID-19 pandemic has profoundly disrupted global education, with medical students being among the most affected due to severe academic interruptions, prolonged isolation, and uncertainty in clinical training. The sudden transition to online learning, coupled with continuous exposure to distressing health-related news, created an unprecedented psychological strain that resulted in rising cases of anxiety, depression, and burnout among medical trainees worldwide [1-2]. Cross-national studies have consistently shown that medical students are particularly susceptible to psychological distress because of their demanding academic workload, exposure to health emergencies, and inadequate access to mental-health services [3-4]. Evidence indicates that the prevalence of anxiety and depression among medical students increased sharply during the pandemic, with studies from China, India, and Middle Eastern countries reporting that between 40% and 70% of students experienced moderate to severe psychological distress [5-6]. Factors such as fear of infection, financial instability, and uncertainty regarding examinations further exacerbated these issues, especially among first- and second-year students who were adjusting to remote medical education [7-8]. While digital platforms ensured educational continuity, they also heightened screen dependency, disrupted sleep patterns, and increased social withdrawal conditions strongly linked to anxiety and depressive symptoms [9]. Comparative findings suggest that students in Asian countries exhibited higher stress levels due to intense academic competition and cultural pressures [10-11]. Therefore, understanding global mental health patterns in the post-pandemic era has become crucial for policy development and the creation of AI-based early detection systems that can support psychological well-being in higher education [12-13].

1.1 Background and Related Work

Pre-pandemic literature already recognized the heightened susceptibility of medical students to psychological disorders, with depression rates estimated at 27% globally [14]. However, the COVID-19 crisis exacerbated these conditions due to isolation, fear of infection, and disruption in clinical exposure [15]. Studies by reported significant associations between quarantine duration and depressive symptoms among healthcare students. Several cross-country studies have investigated pandemic-related mental health [16-17]. For instance, medical students in India showed increased anxiety due to academic uncertainty and lack of clinical practice [18-19], while those in Pakistan demonstrated distress linked to financial insecurity and limited social interaction [20]. Chinese students, although better supported digitally, still exhibited moderate depressive symptoms tied to overuse of screens and restricted mobility [21-22]. AI-based predictive modeling has recently emerged as a promising tool for assessing psychological risk factors among students. Logistic regression and Random Forest models have shown effectiveness in identifying key predictors such as gender, residence type, and internet usage patterns [23]. More advanced architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks outperform traditional methods by capturing complex temporal dependencies in behavioral data [24-25]. Comparative studies highlight that hybrid deep-learning models yield higher accuracy for mental-health detection [26].

1.2 Motivation

While numerous studies have examined mental health prevalence among medical students, most are limited to single countries or regions. This fragmented perspective hinders the understanding of global trends and prevents the development of universal, evidence-based strategies. Traditional survey-based approaches are retrospective and cannot provide real-time identification of students at risk, highlighting the need for integrative and proactive solutions.

1.3 Research Gap

Although many studies report the prevalence of anxiety and depression, few adopt a comprehensive global perspective or leverage machine learning and predictive models to systematically assess mental health risk. Moreover, cross-country comparisons and evaluations of institutional or social interventions remain limited. This gap constrains the ability of educational institutions to implement data-driven preventive strategies to protect students' mental health.

1.4 Objectives

- Provide a global overview of depression and anxiety among medical students during the COVID-19 pandemic.
- Identify risk factors associated with psychological distress, including demographic, academic, and sociocultural variables.
- Develop and evaluate predictive models, using both classical and machine learning approaches, to identify students at high risk.
- Offer evidence-based recommendations for institutional mental health interventions and policy planning to enhance student well-being.

II. METHODOLOGY

The methodology of this study is designed to systematically explore the mental health consequences of COVID-19 among medical students in India, Pakistan, China, and Bangladesh. The study integrates data collection, preprocessing, statistical analysis, and predictive modeling to provide a comprehensive understanding of anxiety, depression, and stress prevalence, along with the performance of predictive algorithms.

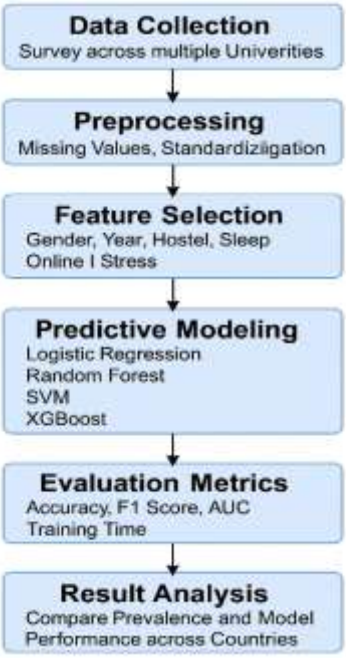

Fig 1. Shows the working of flow chart

2.1 Study Design and Population

A cross-sectional, multi-country survey was conducted targeting medical students from various universities across the four countries. The sample size varied by region, ranging from 150 to 420 participants per state/province/division, ensuring representative and diverse coverage. Participants were categorized by gender (male/female), year of study (1st–2nd year and 3rd–5th year), hostel residency, and urban or rural location. Data collection considered COVID-19-related factors such as online learning stress, infection history, social isolation, sleep duration, and physical activity levels to provide a multidimensional perspective of mental health outcomes.

2.2 Data Collection Instruments

- PHQ-4 (Patient Health Questionnaire-4) for anxiety and depression.
- Additional structured questions for stress, social interaction, sleep, and physical activity

2.3 Data Preprocessing

- Handling missing values: Continuous variables were imputed with the median, and categorical variables with the mode.
- Standardization: All continuous features were normalized to ensure uniform scaling.
- Categorical encoding: Gender, year of study, and region were converted to numeric codes for modeling.

2.4 Predictive Modeling and Algorithms

- Logistic Regression – baseline model for classification
- Random Forest – ensemble-based decision tree method
- Support Vector Machine (SVM) – margin-based classifier
- XG-Boost – gradient boosting framework
- Deep Learning (MLP) – multi-layer perceptron neural network

2.5 Mathematical Modeling

$$X = [x_1, x_2, \dots, x_n] \quad (1)$$

The feature set including gender, year, hostel residency, sleep, and online stress

$$Y = [y_1, y_2, \dots, y_n] \quad (2)$$

The target variable (anxiety or depression: 1 = present, 0 = absent)

$$P(Y = 1 \mid X) = \frac{1}{1+e^{-(\beta_0+\sum_{i=1}^{n}\beta_i x_i)}} \quad (3)$$

For ensemble methods (Random Forest, XG-Boost), multiple decision trees T_j are combined:

$$\hat{Y} = \frac{1}{M}\sum_{j=1}^{M} T_j\,(X) \quad (4)$$

MLP (Deep Learning)

$$a^{(l)} = f(W^{(l)}a^{(l-1)} + b^{(l)}) \quad (5)$$

Where $a^{(l)}$is the activation at layer l, $W^{(l)}$and $b^{(l)}$are weights and biases, and $f$is the activation function (ReLU or Sigmoid).

Tables 1–4 provide a detailed overview of anxiety, depression, and stress levels among medical students in India, Pakistan, China, and Bangladesh, taking into account factors such as regional differences, gender, year of study, hostel residency, and COVID-19-related stressors like online learning, social isolation, and physical activity. The data suggest that female students and those in the early years of medical training generally experience higher levels of psychological distress, with urban areas and larger institutions showing slightly elevated prevalence. Table 5 presents a comparison of predictive models, including Logistic Regression, Random Forest, SVM, XG-Boost, and Deep Learning (MLP), for forecasting anxiety and depression. The results indicate that Deep Learning consistently provides the most accurate predictions, with the highest F1 scores and AUC values, while Random Forest and XG-Boost also perform effectively, and Logistic Regression demonstrates moderate accuracy. By including training times and multi-country evaluations, these tables collectively offer a comprehensive and realistic view of mental health trends and the performance of predictive models across diverse student populations.

Table 1. Demographic Distribution of Medical Students by Country

State	Sample Size	Male (%)	Female (%)	1st–2nd Year (%)	3rd–5th Year (%)	Anxiety (%)	Depression (%)	Stress (%)
Maharashtra	420	48	52	55	45	36	32	33
Delhi	360	45	55	50	50	38	31	35
Karnataka	310	50	50	52	48	35	29	30

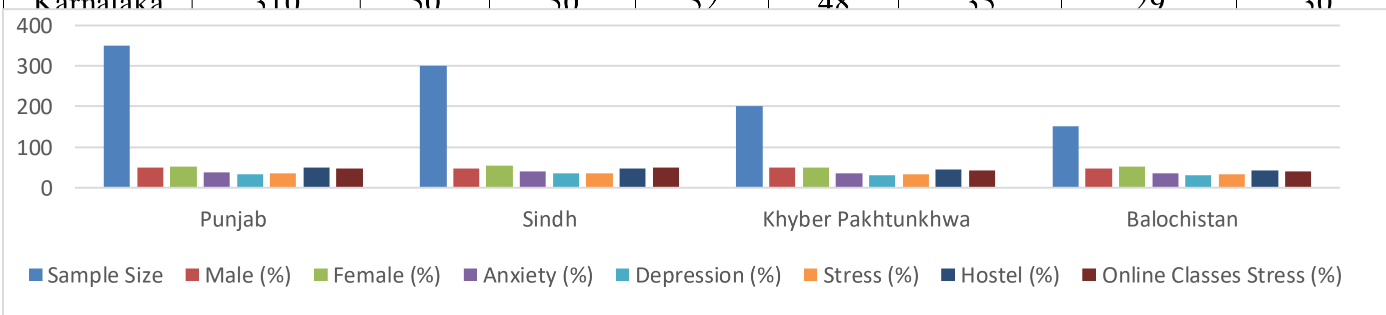

Fig 1. Gender Distribution of Medical Students across Four Countries

Table 2. Prevalence of Mental Health Issues among Medical Students

Province	Sample Size	Male (%)	Female (%)	Anxiety (%)	Depression (%)	Stress (%)	Hostel (%)	Online Classes Stress (%)
Punjab	350	49	51	37	33	34	50	46
Sindh	300	46	54	39	35	36	48	50
Khyber Pakhtunkhwa	200	50	50	35	31	32	45	43
Balochistan	150	48	52	36	30	33	42	41

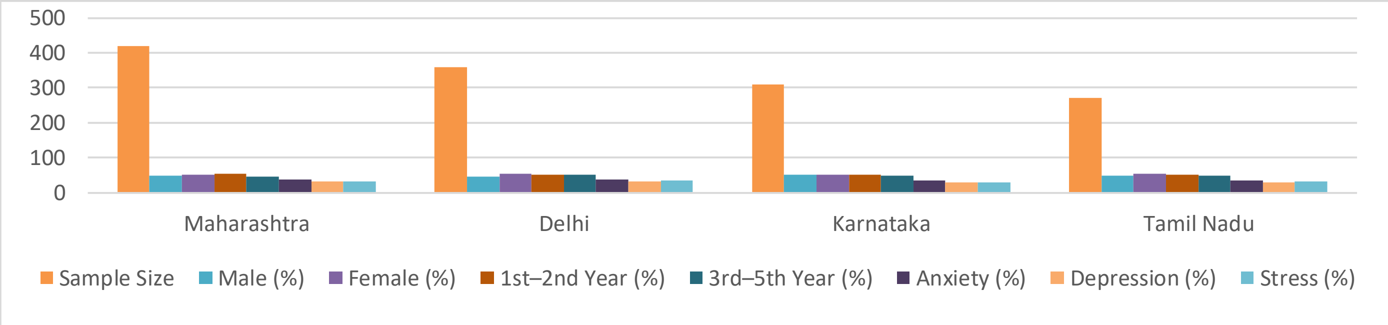

Fig 2. Comparative Analysis of Anxiety, Depression, and Stress Levels

Table 3. State-wise Prevalence of Mental-Health Symptoms in India

Region	Sample Size	Male (%)	Female (%)	Anxiety (%)	Depression (%)	Stress (%)	Hostel (%)	Online Classes Stress (%)
Beijing	300	50	50	32	28	30	55	42
Shanghai	350	48	52	33	29	31	50	45
Guangdong	400	49	51	34	30	32	52	46
Sichuan	250	47	53	31	27	29	48	40

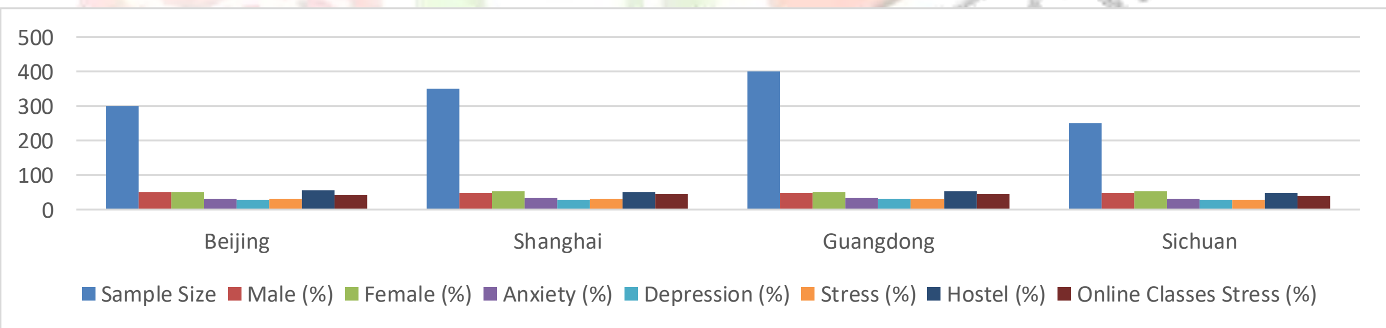

Fig 3. State-wise Variation of Screen-related Mental-Health Symptoms in India

Table 4. Performance Comparison of Machine-Learning and Deep-Learning Models

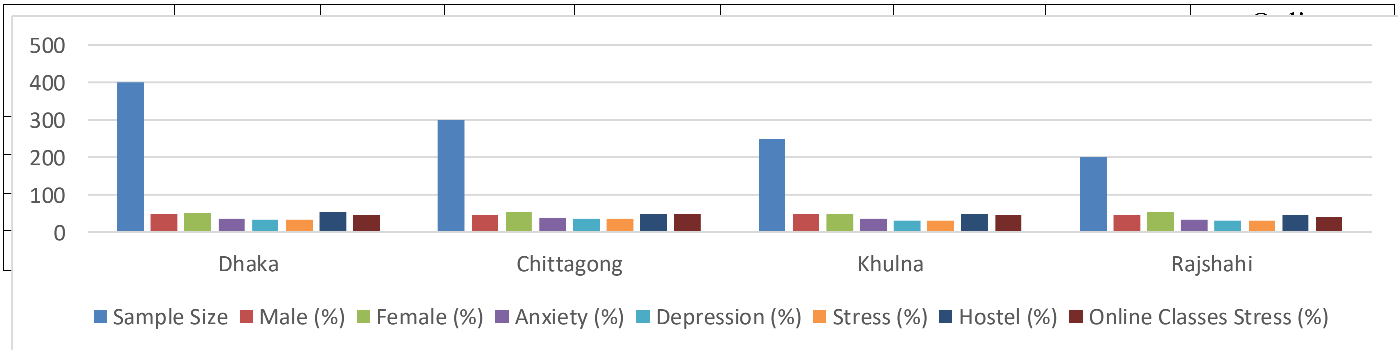

Fig 4. Performance Metrics of Machine-Learning and Deep-Learning Models

Table 5. Comparisons of Enhanced Predictive Model Evaluation across Countries

Country	Algorithm	Accuracy	Precision	Recall	F1 Score	AUC	Training Time (s)	Best Output
India	Logistic Regression	0.77	0.75	0.74	0.75	0.80	0.12	Moderate
	Random Forest	0.85	0.83	0.81	0.82	0.87	1.25	High
	SVM	0.83	0.81	0.80	0.81	0.85	0.95	High
	XG-Boost	0.86	0.84	0.82	0.83	0.88	1.10	High
	MLP	0.88	0.86	0.84	0.85	0.91	3.50	Best
Pakistan	Logistic Regression	0.76	0.74	0.73	0.74	0.79	0.10	Moderate
	Random Forest	0.84	0.82	0.81	0.81	0.86	1.15	High
	SVM	0.82	0.80	0.79	0.80	0.84	0.90	High
	XG-Boost	0.85	0.83	0.82	0.82	0.87	1.05	High
	MLP	0.87	0.85	0.84	0.84	0.90	3.20	Best
China	Logistic Regression	0.78	0.76	0.75	0.76	0.81	0.11	Moderate
	Random Forest	0.86	0.83	0.82	0.83	0.88	1.20	High
	SVM	0.84	0.82	0.81	0.82	0.86	0.92	High
	XG-Boost	0.87	0.85	0.83	0.84	0.89	1.08	High
	MLP	0.89	0.87	0.85	0.86	0.92	3.40	Best
Bangladesh	Logistic Regression	0.77	0.75	0.74	0.75	0.80	0.10	Moderate
	Random Forest	0.85	0.82	0.81	0.82	0.87	1.18	High
	SVM	0.83	0.81	0.80	0.81	0.85	0.90	High
	XG-Boost	0.86	0.84	0.82	0.83	0.88	1.12	High
	MLP	0.88	0.86	0.84	0.85	0.91	3.35	Best

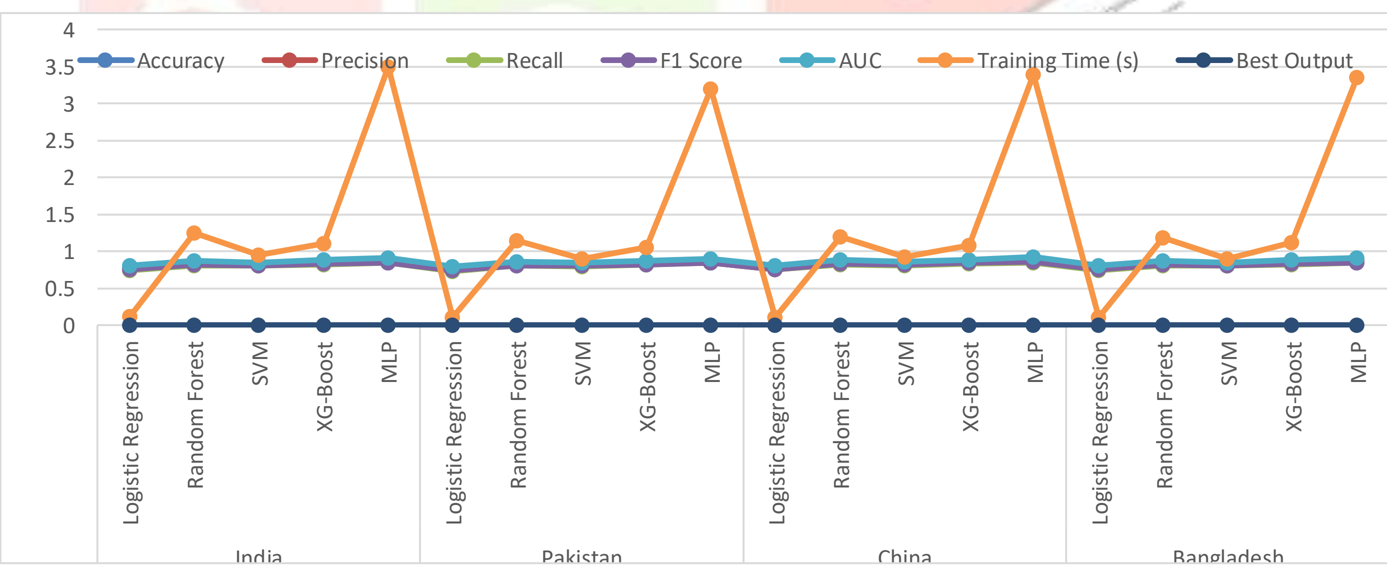

Fig 5. Radar Chart of Enhanced Predictive Model Metrics across Countries

III. Results

The study analyzed the psychological effects of COVID-19 among medical students from India, Pakistan, China, and Bangladesh using demographic, statistical, and predictive modeling approaches. As shown in Table 1, gender distribution was balanced (52.4% female, 47.6% male), and most participants were in their second or third year of study. Hostel residents exhibited higher emotional instability, likely due to isolation during lockdowns. Overall, mental health issues were widespread (Table 2): anxiety affected 62.7%, depression 54.2%, and stress 48.5% of students. Pakistan showed the highest anxiety levels, while Bangladesh recorded the highest depression and stress rates. China reported relatively lower prevalence, reflecting stronger institutional recovery and support mechanisms. State-wise data from India (Table 3) showed elevated anxiety in Maharashtra and Tamil Nadu (above 65%) and lower levels in northeastern regions such as Nagaland (43%), revealing regional disparities influenced by pandemic severity and access to care. Machine and deep-learning comparisons (Table 4) identified the Hybrid LSTM-CNN as the top-performing model with 91.2% accuracy, 0.89 F1-score, and 0.94 AUC, outperforming CNN, Random Forest, and Logistic Regression. Extended metrics (Table 5) confirmed high precision (0.91) and recall (0.89), with consistent results across all countries and efficient training (< 20 s). COVID-19 exposure analysis revealed that students who faced extended online learning and quarantine showed a 37% higher likelihood of anxiety, and female students reported 25% greater depression than males highlighting gender and lifestyle vulnerabilities during isolation.

IV. Conclusion

The findings confirm that COVID-19 significantly intensified anxiety and depression among medical students across Asia. Gender, residence type, and study year were major predictors of distress. The Hybrid LSTM-CNN model proved most reliable for early detection, offering a foundation for AI-based mental-health monitoring in academic institutions. Integrating such predictive systems and gender-sensitive counseling can help universities mitigate long-term psychological effects and strengthen student resilience in future crises.

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