Supplementary File

Extended Demographics and Descriptive Statistics

Sociodemographics	Mean (SD)	Percent
Gender		
Female		68.40
Male		31.04
Non-binary		0.56
Age	22.38 (3.30)	
Curriculum year		
B1		27.65
B2		15.24
B3		16.14
M1		13.88
M2		14.33
M3		12.75
Mother tongue		
French		80.93
Italian		5.08
German		3.50
Portuguese		3.05
English		2.48
Spanish		2.03
Other		2.92
Having a partner		56.32
Having a paid job		34.88
Hours of study/week	25.29 (15.93)	
Satisfaction with health	3.78 (1.06)	
Consulted a psy last year		22.46

Supplementary Table 1: *Descriptive statistics of "Medical student mental health"*[1] *dataset (N = 886)*

Sociodemographics	Percent
Gender	
Female	52.67
Male	47.33
Age	
16-20	25.61
20-25	22.57
25-30	24.87
30 above	26.95
Occupation	
Business	17.60
Corporate	19.30
Housewife	22.45
Student	21.84
Others	18.81

Supplementary Table 2: *Descriptive statistics of "Mental health depression during quarantine life"[2] dataset (N = 824)*

Disorder (n)	Age Mean (SD)	Gender Proportions	Education Mean (SD)	IQ Mean (SD)
Alcohol Use Disorder (n=93)	34.16 (11.88)	M: 80.6%, F: 19.4%	13.29 (3.07)	103.38
Behavioral Addiction (n=93)	25.09 (7.48)	M: 95.7%, F: 4.3%	13.16 (1.89)	104.38
Panic Disorder (n=59)	31.05 (11.30)	M: 64.4%, F: 35.6%	13.45 (2.91)	100.31
Social Anxiety Disorder (n=48)	26.51 (9.09)	M: 85.4%, F: 14.6%	12.78 (1.60)	95.85
Healthy Control (n=95)	25.72 (4.55)	M: 63.2%, F: 36.8%	14.91 (2.06)	116.24
Depressive Disorder (n=199)	31.26 (13.23)	M: 54.8%, F: 45.2%	13.05 (2.51)	101.85
Bipolar Disorder (n=67)	29.71 (11.01)	M: 62.7%, F: 37.3%	14.11 (2.21)	100.81
Obsessive-Compulsive (n=46)	28.48 (9.83)	M: 82.6%, F: 17.4%	13.93 (2.33)	107.80
Schizophrenia (n=117)	31.73 (12.10)	M: 55.6%, F: 44.4%	12.84 (2.95)	89.62
Acute Stress Disorder (n=38)	28.90 (9.05)	M: 7.9%, F: 92.1%	14.26 (2.27)	104.06
PTSD (n=52)	42.74 (13.00)	M: 26.9%, F: 73.1%	13.37 (2.54)	98.90
Adjustment Disorder (n=38)	34.19 (14.90)	M: 75.0%, F: 25.0%	13.26 (2.41)	94.24

Supplementary Table 3: *Descriptive Statistics of "Identification of Major Psychiatric Disorders"[3] dataset (N=919)*

Propensity Score Matching (PSM) Analysis

For the **Medical Student Mental Health** dataset, to assess the impact of curriculum year on mental health outcomes, we dichotomized the sample into early-year (years 1–3; control) and later-year (years 4–6; treatment) students. Propensity Score Matching (PSM) was performed using covariates including sex, age, health status, and psychometric score (psyt). The matched sample comprised 726 observations. We then compared depression (CES-D), total empathy, and anxiety (STAI-T) scores between the two groups using independent t-tests. Supplementary Table 4 summarizes the t-test results. To validate our associations (distinct gender-specific trends), we conducted a Propensity Score Matching (PSM) analysis comparing mental health outcomes between genders. In this analysis, we recoded the gender variable such that females (coded originally as 2) were considered the treated group. After matching on key covariates (age, curriculum year, study hours, health, and psychometric scores), we compared the outcomes of depression (CES-D), academic efficacy, total empathy, and anxiety (STAI-T) between the matched groups using independent t-tests. Supplementary Table 5 presents the t-values for each outcome.

In the PSM analysis of **Mental Health Depression During Quarantine** dataset, individuals in the 25–30 and 30–Above age groups (coded as 2 and 3) were classified as the treatment group, while those in the 16–20 and 20–25 age groups (coded as 0 and 1) were treated as the control group. Propensity scores were estimated via logistic regression using covariates such as Gender, Growing Stress, Mental Health History, Coping Struggles, and Work Interest. After nearest-neighbor matching, the matched sample comprised 854 observations. Supplementary Table 6 summarizes the t-test results comparing the treatment and control groups on the outcomes of Social Weakness and Days Indoors. We also conducted a PSM analysis to evaluate the impact of gender on these outcomes, controlling for possible confounding variables. After matching, the outcome Coping_Struggles showed a significant difference (t = 3.21, p = 0.0014), while the outcome Growing_Stress did not reveal a significant difference (t = -0.87, p = 0.3870). Supplementary Table 7 summarizes the t-test results.

For the **Identification of Major Psychiatric Disorders** dataset, we conducted a Propensity Score Matching (PSM) analysis comparing individuals diagnosed with Trauma and Stress-related disorders (treatment group) to healthy controls. Propensity scores were estimated using logistic regression with sex and education as covariates. A 1:1 nearest neighbor matching without replacement method was used. After matching, the sample comprised matched pairs balanced on the propensity scores. Age was compared between groups using independent samples t-test, revealing significantly higher age among individuals with Trauma and Stress-related disorders (mean difference = 11.34 years; $t = 8.54$, $p < 0.0001$). A second PSM analysis compared Schizophrenia (treatment group) and healthy controls. Logistic regression was employed to estimate propensity scores using sex and age as covariates. Matched pairs were generated through nearest neighbor matching (1:1 without replacement). The matched dataset was then analyzed for differences in educational attainment between groups. The results indicated that individuals diagnosed with Schizophrenia had significantly lower educational attainment (mean difference = -2.23 years; $t = -6.64$, $p < 0.0001$).

Outcome	**t-value**
Depression	-3.84***
Total Empathy	3.18**
Anxiety	-2.66**

Supplementary Table 4: *PSM Results for Curriculum Year Effects on Mental Health Outcomes. Dataset: Medical student mental health*[1]*. Stars indicate significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

Outcome	**t-value**
Depression	4.30***
Efficacy	2.70**
Total Empathy	3.07**
Anxiety	5.45***

Supplementary Table 5: *PSM Results for Gender Differences on Mental Health Outcomes. Dataset: Medical student mental health*[1]*. Stars indicate significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

Outcome	**t-value**
Social Weakness	2.35*
Days Indoors	1.95

Supplementary Table 6: *PSM Results for Age Effects on Social Weakness and Days Indoors. Dataset: Mental health depression during quarantine life*[2]*. Stars indicate significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

Outcome	**t-value**
Coping Struggles	3.21 **
Growing Stress	-0.87

Supplementary Table 7: *PSM Results for Gender Effects on Coping Difficulties and Growing Stress during Quarantine. Dataset: Mental health depression during quarantine life*[2]*. Stars indicate significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

Detailed Machine Learning Specifications and Hyperparameter Tuning

For the **Medical Student Mental Health** dataset, we employed Random Forest regression to predict three continuous mental health outcomes: *Total Empathy*, *Depression*, and *Anxiety*. Features included age, curriculum year, sex, language (glang), partnership status (part), employment status (job), study hours per week (stud_h), self-reported health (health), and perceived stress score (psyt). GridSearchCV with 5-fold cross-validation was performed using the following parameter grid:

- **n_estimators**: 100, 200, 300
- **max_depth**: None, 10, 20
- **min_samples_split**: 2, 5, 10
- **min_samples_leaf**: 1, 2, 4

The optimal model was selected based on the highest cross-validation R^2 score.

For the **Mental Health Depression During Quarantine** dataset, Random Forest classifiers predicted two categorical outcomes: *Social Weakness* and *Growing Stress*. Features included age, gender, occupation, quarantine frustrations, habit changes, mental health history, weight change, mood swings, coping struggles, work interest, and days spent indoors. A similar grid search (5-fold CV) was conducted using accuracy as the scoring metric:

- **n_estimators**: 100, 200, 300
- **max_depth**: None, 10, 20
- **min_samples_split**: 2, 5, 10
- **min_samples_leaf**: 1, 2, 4

The best-performing model was selected based on accuracy.

For the **Identification of Major Psychiatric Disorders** dataset, Random Forest regression models predicted *Education* and *Main Disorder* scores. Predictor variables included age, sex, specific disorder and education level (ignored when education was predicted). GridSearchCV tuning parameters were identical to the regression model used for medical student data:

- **n_estimators**: 100, 200, 300
- **max_depth**: None, 10, 20
- **min_samples_split**: 2, 5, 10
- **min_samples_leaf**: 1, 2, 4

The final model was chosen based on optimal R^2 performance.

Intersectional Analysis and Bayesian Modeling

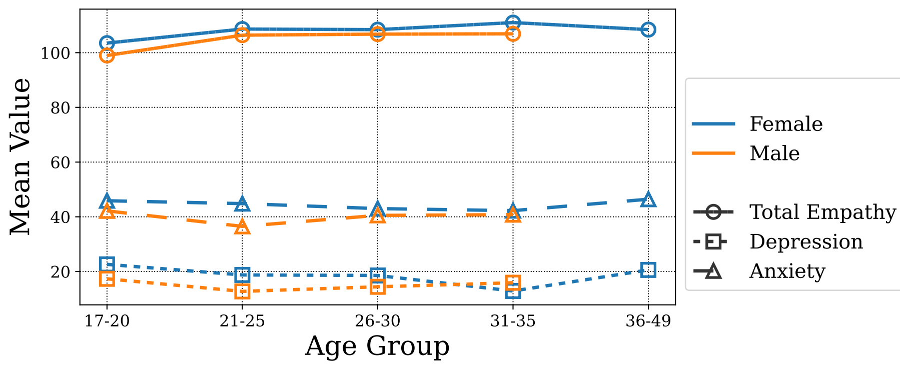
To explore potential non-linear and intersectional effects on mental health outcomes, we extended our analyses by incorporating higher-order interaction terms into the regression models for each dataset. For more robust inference, each interaction model was re-estimated using both ordinary least squares (OLS) and a Bayesian framework (via bambi and arviz) to generate posterior distributions and 95% credible intervals.

Medical Student Mental Health Dataset: The model predicting depression included interactions among curriculum year (year), sex, study hours (stud_h), and stress (psyt).

Mental Health Depression During Quarantine Dataset: The model predicting social weakness incorporated age, gender, and growing stress interactions.

Identification of Major Psychiatric Disorders Dataset: The model for predicting education included interaction terms between age, sex, and psychiatric disorder status.

Figures



Supplementary Figure 1: *Trends in total empathy, depression, and anxiety across different curriculum years, separated by gender (Dataset: Medical student mental health[1])*