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Article

Machine Learning and Differential Equation-Based Epidemic Model Framework for Predicting Student Burnout and Depression Due to Academic Workload During and Post-Pandemic.

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Abstract: The rapid increase in academic workload during and after the COVID-19 pandemic has significantly affected the mental health of university students, leading to higher incidences of burnout and depression. Traditional statistical methods provide valuable insights into the relationships between academic and psychological variables but are often inadequate for capturing complex nonlinear interactions and forecasting the temporal progression of mental health conditions. This study proposes a novel Machine Learning and Differential Equation-Based Epidemic Model Framework for predicting student burnout and depression resulting from academic workload. Initially, statistical analyses, including descriptive statistics, correlation analysis, and regression techniques, are employed to identify significant academic, behavioral, and psychological factors influencing student mental health. Subsequently, an Artificial Neural Network (ANN) is developed to learn nonlinear relationships between these factors and to accurately predict individual burnout and depression levels. The ANN-predicted outcomes are then integrated into a compartmental epidemic-inspired differential equation model, where the transition parameters are dynamically estimated rather than assumed constant. The proposed mathematical model describes the temporal evolution of healthy, burnout, depressed, and recovered student populations under varying academic conditions. Numerical simulations are performed using synthetic and survey-based datasets to investigate the effects of workload intensity and intervention strategies on student mental health. The results indicate that combining ANN with differential equation modeling provides both high prediction accuracy and mathematical interpretability while enabling long-term forecasting of burnout and depression dynamics. The proposed framework offers an effective decision-support tool for educational institutions to implement early intervention strategies, optimize academic policies, and promote student psychological well-being.

Keywords: Student Burnout, Depression Prediction, Academic Workload, Artificial Neural Network (ANN), Machine Learning, Differential Equation Model, Epidemic Modeling, Mental Health Prediction

1. Introduction

The COVID-19 pandemic has fundamentally transformed higher education by shifting traditional classroom teaching to online and hybrid learning environments. Although these changes ensured academic continuity, they also increased academic workload, prolonged screen exposure, social isolation, and psychological stress among students. Even in the post-pandemic period, universities continue to employ blended learning strategies, resulting in sustained academic pressure and mental health challenges. Consequently, student burnout and depression have emerged as major concerns affecting academic performance, emotional well-being, learning outcomes, and future career development.

Student burnout is characterized by emotional exhaustion, academic disengagement, and reduced personal accomplishment resulting from prolonged exposure to educational stressors. Depression is another serious psychological condition associated with persistent sadness, lack of motivation, impaired concentration, and reduced cognitive functioning. Recent studies have reported increasing rates of burnout and depression among university students, with academic workload, insufficient sleep, excessive screen time, lack of physical activity, and limited social interaction identified as significant contributing factors.

Traditional statistical approaches, such as descriptive statistics, correlation analysis, and multiple regression, have been extensively used to identify relationships between academic workload and psychological outcomes. While these methods provide valuable insights into significant predictors, they generally assume linear relationships and often fail to capture the complex nonlinear interactions among behavioral, academic, and psychological variables. Consequently, their predictive capability is limited when analyzing large and heterogeneous datasets.

Machine learning techniques have recently gained considerable attention in mental health research because of their ability to model complex nonlinear relationships and improve predictive accuracy. Among these techniques, Artificial Neural Networks (ANNs) have demonstrated remarkable performance in healthcare, psychology, and educational data mining by learning hidden patterns from multidimensional datasets. ANNs can accurately predict burnout and depression risks using demographic, academic, behavioral, and psychological features without requiring explicit mathematical assumptions about the relationships among variables.

Although ANN models provide accurate predictions, they function primarily as data-driven models and often lack the ability to describe how burnout and depression evolve over time. In contrast, compartmental differential equation models describe the temporal dynamics of populations by dividing individuals into different states and analyzing transitions between them. Inspired by epidemic models, student mental health can be represented using compartments such as healthy students, students experiencing burnout, depressed students, and recovered students. Such mathematical models enable researchers to investigate the progression of mental health conditions and evaluate the long-term effects of intervention strategies.

Integrating machine learning with differential equation models provides a promising hybrid framework that combines the predictive strength of ANN with the interpretability and temporal forecasting capability of mathematical modeling. In the proposed framework, ANN is employed to estimate burnout and depression risks from survey data, while these predictions are used to determine dynamic transition parameters in the compartmental differential equation model. This integration allows personalized and time-dependent prediction of mental health dynamics instead of relying on fixed transition parameters.

The proposed study develops a Machine Learning and Differential Equation-Based Epidemic Model Framework for predicting student burnout and depression associated with academic workload during and after the pandemic. The framework integrates statistical analysis, ANN, and a compartmental differential equation model to identify influential factors, predict individual mental health risks, and simulate their evolution over time. The proposed model provides a comprehensive mathematical tool for early warning systems, educational policy planning, and timely psychological interventions in higher education institutions.

Student burnout has become a major concern in higher education, particularly after the COVID-19 pandemic. Burnout is characterized by emotional exhaustion, academic disengagement, and reduced academic efficacy. Recent studies [1] indicate that increased academic workload, prolonged online learning, social isolation, inadequate sleep, and psychological stress significantly increase burnout among university students. Systematic reviews have shown that burnout prevalence increased during the pandemic across different countries and academic disciplines, emphasizing the need for early detection and intervention strategies. The development of the Study Demands–Resources (SD–R) Theory further explains that high study demands (e.g., examinations, assignments, time pressure) combined with insufficient resources (e.g., social support, coping skills) lead to burnout and poor academic outcomes. This theoretical framework [2] has become one of the most widely accepted models for understanding student well-being in higher education.

Depression has emerged as one of the most prevalent psychological disorders among university students. Numerous investigations [3] have reported strong associations between academic workload, anxiety, sleep deprivation, burnout, and depression. Burnout often precedes depressive symptoms, suggesting that persistent academic stress may progressively develop into more severe mental health conditions. Recent studies have also demonstrated that social support acts as a protective factor, reducing both burnout and depression among students. Most early investigations employed descriptive statistics, Pearson correlation, multiple regression, structural equation modeling (SEM), logistic regression, and analysis of variance to identify factors influencing burnout and depression. These methods [4] successfully identified significant predictors such as academic workload, sleep duration, stress level, social support, and physical activity. However, because they primarily assume linear relationships, they often fail to capture the complex nonlinear interactions present in educational and psychological datasets. Consequently, their predictive performance may be limited when applied to large and heterogeneous student populations.

Artificial intelligence and machine learning have [5] increasingly been applied to mental health prediction because of their ability to model nonlinear relationships. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests, Decision Trees, and Extreme Gradient Boosting (XGBoost) have demonstrated higher predictive accuracy than conventional statistical techniques for identifying students at risk of anxiety, depression, and burnout. Bibliometric analyses also indicate rapidly increasing research interest in AI-assisted mental health assessment, particularly after the COVID-19 pandemic. Although ANN models achieve high prediction accuracy, most studies treat them as black-box predictive tools without integrating them into mathematical models capable of describing temporal evolution.

Compartmental differential equation models have traditionally been used to study infectious disease transmission. More recently, similar mathematical frameworks have been adapted to model the spread of behavioral and psychological conditions by considering transitions among different population states. These models provide insight into the temporal evolution of systems, equilibrium analysis, stability, and intervention effects. However, most existing models employ constant transition parameters that do not account for individual differences or dynamically changing academic conditions. Furthermore, research on mathematical modeling of student burnout remains limited, despite the conceptual similarity between psychological contagion and epidemic spreading processes.

Recent developments in computational science have emphasized combining machine learning with differential equation models. Hybrid approaches [6] exploit the predictive capability of machine learning while preserving the interpretability and mechanistic understanding provided by mathematical models. Such integrations have been successfully applied in biomedical engineering, disease modeling, biomechanics, and biological systems, where machine learning estimates unknown model parameters and differential equations describe system dynamics. However, only a few studies have attempted similar hybrid frameworks for educational psychology, and almost none have combined Artificial Neural Networks with epidemic-inspired differential equations to model student burnout and depression. The literature reveals several important limitations. Most studies rely on statistical analyses or machine learning independently rather than integrating both approaches. Existing machine learning models mainly focus on classification or prediction and do not explain the temporal progression of burnout and depression. Differential equation models generally use fixed transition parameters, ignoring the dynamic variability among students. Very few studies combine Artificial Neural Networks with compartmental differential equations for educational mental health prediction. Existing investigations rarely provide a unified framework capable of identifying significant predictors, estimating personalized transition parameters, and forecasting long-term burnout and depression dynamics.

Therefore, there is a need to develop a hybrid Machine Learning and Differential Equation-Based Epidemic Model in which statistical analysis identifies influential factors, ANN predicts individualized burnout and depression risks, and the predicted outcomes are incorporated into a compartmental differential equation model for dynamic forecasting and intervention analysis. The increasing prevalence of burnout and depression among university students has become a major educational and public health concern. Although many institutions collect student mental health data, few studies combine predictive machine learning with dynamic mathematical modeling to understand both who is at risk and how the risk evolves over time. This motivates the development of an integrated framework capable of supporting early intervention and evidence-based decision making.

Although considerable research has been conducted on student mental health, several important gaps remain:

1. Most existing studies rely on statistical analyses or conventional regression models that assume linear relationships and have limited predictive capability.

2. Existing machine learning models mainly focus on prediction accuracy but rarely explain the temporal evolution of burnout and depression.

3. Most compartmental mathematical models employ constant transition parameters, which do not reflect differences in individual student characteristics or changing academic environments.

4. Very few studies integrate statistical analysis, Artificial Neural Networks, and compartmental differential equations into a unified framework for student mental health prediction.

5. Existing research often concentrates on either burnout or depression separately rather than modeling their interaction and progression.

6. Limited attention has been given to forecasting mental health dynamics during and after the COVID-19 pandemic under varying academic workloads.

7. There is a lack of mathematically interpretable hybrid models that can assist universities in designing timely intervention strategies based on predicted student risk.

To develop a hybrid machine learning and differential equation-based epidemic model that accurately predicts student burnout and depression and analyzes their temporal evolution under varying academic workload conditions.

The specific objectives of this study are:

1. To collect and preprocess academic, behavioral, lifestyle, and psychological data from university students.

2. To identify statistically significant factors associated with burnout and depression using descriptive and inferential statistical analyses.

3. To develop an Artificial Neural Network for predicting individual burnout and depression levels.

4. To formulate a compartmental differential equation model representing transitions among healthy, burnout, depressed, and recovered student populations.

5. To estimate dynamic transition parameters of the differential equation model using ANN predictions.

6. To perform numerical simulations for analyzing the temporal evolution of student mental health.

2. Preliminary Concepts

2.1 Student Burnout

Student burnout is a psychological condition resulting from prolonged exposure to academic stress and excessive workload. It is characterized by emotional exhaustion, reduced academic motivation, and decreased learning efficiency. During and after the COVID-19 pandemic, online learning, social isolation, and increased academic expectations significantly increased burnout levels among students.

Burnout is commonly measured using standardized instruments such as:

Maslach Burnout Inventory–Student Survey (MBI-SS)

Copenhagen Burnout Inventory (CBI)

Oldenburg Burnout Inventory (OLBI)

The burnout score is considered one of the main response variables in this study.

2.2 Depression

Depression is a common mental health disorder characterized by persistent sadness, lack of interest, reduced concentration, fatigue, and feelings of hopelessness.

Common assessment scales include

PHQ-9 (Patient Health Questionnaire)

Beck Depression Inventory (BDI)

CES-D Scale

The PHQ-9 score is used as the depression indicator in this work.

2.3 Academic Workload

Academic workload refers to the cumulative educational demands placed on students.

Typical workload indicators include

Study hours per day

Number of assignments

Examination frequency

Online class duration

Project submissions

Laboratory work

Screen time

These variables act as predictors in the machine learning model.

2.4 Epidemic Modeling

Although burnout is not an infectious disease, psychological stress can spread through social interactions, peer influence, and shared academic environments. Therefore, epidemic models provide a useful framework for describing transitions between mental-health states.

Students are divided into four compartments:

(S(t)): Healthy students

(B(t)): Students experiencing burnout

(D(t)): Students with depression

(R(t)): Recovered students

The total student population is

N=S+B+D+R.

The compartmental approach enables analysis of how students move between mental-health states over time.

2.5 Ordinary Differential Equations (ODEs)

An ordinary differential equation describes the rate of change of a variable with respect to time.

General form

$$\frac{dx}{dt} = f(x,t).$$

In this research, the variables S(t),B(t),D(t),R(t) are governed by a system of coupled ODEs, which capture the temporal evolution of burnout and depression.

2.6 Artificial Neural Networks (ANN)

Artificial Neural Networks are computational models inspired by the structure of the human brain. They consist of interconnected neurons organized into layers.

The ANN architecture used in this work contains:

Input layer

Hidden layers

Output layer

Each neuron computes

$$z = \sum_{\{i=1\}}^{\{n\}} w_i x_i + b,$$

followed by an activation function a=f(z).

The ANN learns nonlinear relationships between academic workload and psychological outcomes by adjusting its weights during training.

2.7 Activation Functions

Activation functions introduce nonlinearity into the ANN.

ReLU $f(x) = max(0, x)$

Advantages:

Fast convergence

Reduced vanishing-gradient problem

2.8 Loss Function

The ANN is trained by minimizing the prediction error.

The Mean Squared Error (MSE) loss is

$MSE = 1/N \sum_{\{i=1\}}^{\{N\}} \quad (y_i - \hat{y_i})^2,]$

where (y_i) is the observed value and $(\hat{y_i})$ is the ANN prediction.

2.9 Optimization Algorithm

The Adam optimizer is employed to update the network weights.

Weight update

$$w_{\{new\}} = w_{\{old\}} - \eta\{\partial L\}/\{\partial w\},$$

Where (L): loss function, (η): learning rate.

Adam combines the benefits of momentum and adaptive learning rates, making it effective for nonlinear optimization.

2.10 Data Normalization

Machine learning algorithms perform better when input features are on similar scales.

Min–Max normalization transforms data to the interval ([0,1]):

$$x' = x - \frac{x_{\{min\}}}{\{x_{\{max\}} - x_{\{min\}}\}}.$$

This prevents variables with large numerical ranges from dominating the learning process.

2.11 Performance Metrics

The predictive performance of the ANN is evaluated using several metrics.

Root Mean Square Error

$$RMSE = \surd\{1/N \sum (y_i - \hat{y_i})^2\}$$

Lower values indicate better prediction accuracy.

Mean Absolute Error

$$MAE = 1/N \sum y_i - \hat{y_i}$$

This measures the average prediction error.

2.12 Statistical Concepts

Before training the ANN, exploratory statistical analysis is performed. Mean-Measures the central tendency. Standard Deviation-Measures data variability. Pearson Correlation- This identifies linear relationships between predictors and outcomes.

2.13 Hybrid ANN–Differential Equation Framework

The key novelty of the proposed model is the integration of machine learning with mathematical modeling.

The ANN predicts the burnout and depression levels based on student-specific features. These predictions are then used to estimate the transition parameters of the compartmental differential equation model, allowing the rates to vary dynamically rather than remaining fixed.

Hypotheses

H_{01}: Academic workload has no significant effect on student burnout and depression.

H_{11}: Academic workload significantly affects student burnout and depression.

H_{02}: The proposed ANN–differential equation framework does not improve prediction compared with traditional statistical models.

H_{12}: The proposed ANN–differential equation framework significantly improves prediction accuracy and forecasting capability.

2.14 Numerical Simulation

The coupled differential equations generally do not admit closed-form solutions. Therefore, numerical integration methods such as the fourth-order Runge–Kutta (RK4) method are employed to simulate the trajectories of (S(t)), (B(t)), (D(t)), and (R(t)) over an academic semester. The simulations enable investigation of how different intervention strategies—such as reducing academic workload or increasing counseling support—affect the evolution of student mental health.

3. Methodology

Research Framework

The proposed methodology consists of six major phases.

- Student Survey Data
- Data Collection
- Statistical Analysis
- Data Preprocessing
- Artificial Neural Network
- Differential Equation Model
- Prediction and Performance Evaluation

Phase 1: Data Collection

Step 1.1 Student Survey

Collect data from undergraduate and postgraduate students using standardized psychological questionnaires.

Sample Size

Number of students = 1000

Age = 18–25 years

Universities = Multiple institutions

Study period = During and post-pandemic

Step 1.2 Input Variables

Collect the following variables.

Variable	Description	Variable	Description
Age	Years	Exercise frequency	Physical activity
Gender	Male/Female	Social interaction score	Mental well-being
Study hours/day	Academic workload	Stress score	Psychological factor
Assignments/week	Academic pressure	Anxiety score	Mental health
Online learning hours	Screen exposure	Burnout score	Target variable

Sleep hours	Lifestyle	Depression score	Target variable

Phase 2: Statistical Analysis

The collected data are analyzed statistically before applying machine learning.

Step 2.1 Descriptive Statistics

Compute

Mean

Median

Standard deviation

Variance

Minimum

Maximum

Step 2.2 Correlation Analysis

Calculate Pearson correlation coefficient.

Purpose

Identify variables strongly associated with burnout and depression.

Step 2.3 Regression Analysis

Perform multiple linear regression.

Purpose

Determine statistically significant predictors.

Phase 3: Data Preprocessing

Before ANN training, preprocess the data.

Step 3.1 Missing Value Handling

Replace missing values using

Mean

Median

KNN Imputation

Step 3.2 Normalization

Normalize all features.

Min-Max normalization

Purpose

Improve ANN convergence.

Step 3.3 Dataset Splitting

Training-80%

Testing-20%

Phase 4: Artificial Neural Network

The ANN learns nonlinear relationships between academic workload and mental health.

ANN Architecture

Input Layer-7 neurons

Study hours

Assignments

Sleep
Exercise
Screen time
Stress
Social support
Hidden Layer 1
64 neurons
Activation
ReLU
↓
Hidden Layer 2
32 neurons
Activation
ReLU
↓
Output Layer
2 neurons
Burnout prediction
Depression prediction
Mathematical Representation
Input

$$X = (x_1, x_2, \dots, x_n)$$

Hidden layer

$$H_1 = f(W_1 X + b_1)$$

Second hidden layer

$$H_2 = f(W_2 H + b_2)$$

Output

$$Y = W_3 H_2 + b_3$$

Where

$$Y = (\hat{B}, \hat{D})$$

Loss Function-Mean Squared Error MSE
Optimizer- Adam
Learning rate-0.001
Epochs-200

Phase 5: Differential Equation Model

The ANN outputs are incorporated into an epidemic-style compartmental model.

Define:

(S(t)): Healthy students
(B(t)): Students experiencing burnout
(D(t)): Students with depression
(R(t)): Recovered students

The governing system is

$$\frac{\{dS\}}{\{dt\}} = -\beta\, SB - \eta\, SD + \delta\, R,$$
$$\frac{\{dB\}}{\{dt\}} = \beta\, SB + \alpha\, B + \gamma\, B,$$
$$\frac{\{dD\}}{\{dt\}} = \gamma\, B + \mu\, D,$$
$$\frac{\{dR\}}{\{dt\}} = \alpha\, B + \mu\, D - \delta\, R.$$

ANN–Model Coupling

Instead of using fixed parameters

$$\beta = \beta(\hat{B}\ ), \gamma = \gamma(\widehat{D}),$$

This allows the transition rates to adapt to the characteristics of the surveyed student population.

Phase 6: Numerical Simulation

Solve the differential equations using numerical methods such as the fourth-order Runge–Kutta (RK4) method.

Simulation period:

12 weeks

24 weeks

One academic semester

Outputs include:

Healthy students

Burnout students

Depressed students

Recovered students

Phase 7: Performance Evaluation

Evaluate the ANN using:

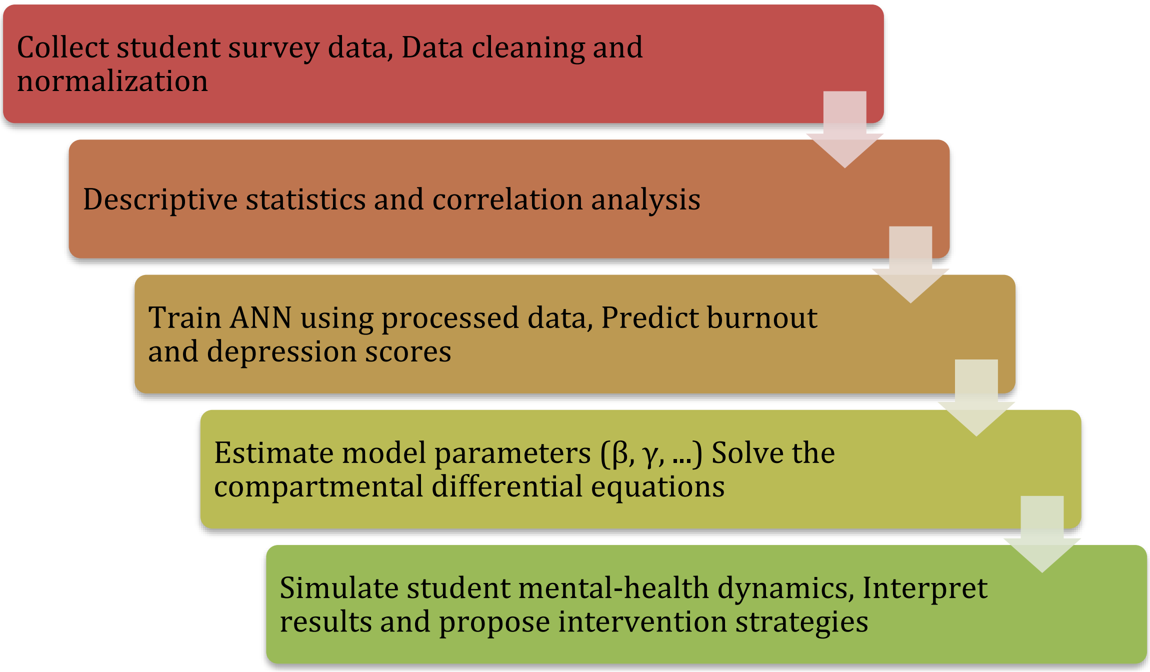
Root Mean Square Error-RMSE

Mean Absolute Error- MAE

Phase 8: Visualization

Generate figures to interpret the results:

Algorithm



4. Example

Suppose we survey 1000 university students. For each student, collect the following information. Variables are Age, Gender, Study hours/day, Assignments/week, Sleep hours Screen time, Exercise, Social interaction score, Anxiety score, Depression score, Burnout score.

Step 1 Statistical Analysis

Suppose the collected data give the mean and SD as follows:

Study hours 8.2 2.3 ;

Sleep 5.6 1.4 ;

Burnout score 64 15 ;

Depression score 13 5 ;

Correlation Analysis

Compute Pearson correlation.

Study hours vs Burnout 0.81

Sleep vs Burnout -0.72

Assignments vs Depression 0.75

Exercise vs Depression -0.61

Interpretation

More study hours increase burnout.

More sleep reduces burnout.

Exercise decreases depression.

Step 2 Multiple Linear Regression

Assume Y={Burnout}

Independent variables- Study hours, Sleep, Assignment load, Exercise.

Regression equation

$$Y = 15 + 4.5X_1 + 2.8X_2 + 3.1X_3 + 1.6X_4$$

Suppose Student studies 8 hours/day, Sleep 5 hours Assignments,-7/week,Exercise-1 day/week

Prediction

Y=15+4.5(8)2.8(5)+3.1(7)+1.6(1)

Y= 15+36-14+21.7-1.6=57.1

Predicted burnout=57.1

Step 3 Logistic Regression

Suppose

Burnout

High =1

Low =0

Logistic model

$$P = \frac{1}{\{1 + e^{\{-Z\}}\}}$$

Where [Z=-4+0.65({Study Hours})+0.52({Sleep})+.44({Depression})]

Suppose

Study=9,Sleep=5,Depression=14

Then

Z=-4+5.85-2.6+6.16=5.41

P=0.995

Meaning

99.5% probability of severe burnout.

Step 4 Machine Learning

Split

Training-80%

Testing-20%

Train

Random Forest

XGBoost

ANN

Suppose Model and Accuracy are

Decision Tree	82%
Random Forest	90%
SVM	91%
ANN	95%

ANN performs best.

Step 5 Differential Equation Model

Instead of disease spread, burnout spreads through academic interaction.

Define

(S(t)): Healthy students

(B(t)): Burnout students

(D(t)): Depressed students

(R(t)): Recovered students

Total

N=S+B+D+R

Model

$$\frac{\{dS\}}{\{dt\}} = -\beta\, SB - \eta\, SD + \delta\, R$$

Healthy students become burnt out after interacting with burnt-out peers.

$$\frac{\{dB\}}{\{dt\}} = \beta\, SB + \alpha\, B + \gamma\, B$$

Burnout students either recover or develop depression.

$$\frac{\{dD\}}{\{dt\}} = \gamma\, B + \mu\, D$$

Depressed students recover slowly.

$$\frac{\{dR\}}{\{dt\}} = \alpha\, B + \mu\, D - \delta\, R$$

Recovered students may again become stressed after returning to academic pressure.

Example Parameters

Suppose $\beta = 0.32$, academic workload transmission $\alpha = 0.10$, burnout recovery $\gamma = 0.18$, burnout→depression $\mu = 0.08$, depression recovery $\delta = 0.03$ relapse

Initial conditions S(0)=900, B(0)=70,D(0)=20,R(0)=10

Numerical Simulation

Suppose after solving,

Week	Healthy	Burnout	Depression	Recovered
0	900	70	20	10
2	820	120	40	20
4	690	190	75	45
6	610	180	120	90
8	640	140	100	120
10	710	95	70	125

Interpretation

Burnout rises first, peaks around weeks 4–6, then declines as students recover.

Step 6 Coupling Statistics with the Differential Equation

Rather than treating (β) as a constant, estimate it from the survey data.

For example, $\beta = 0.02(\{Study\ Hours\}) + 0.04(\{Assignment\ Load\}) - 0.03(\{Sleep\})$

Suppose a student has Study = 8 hours, Assignments = 6/week, Sleep = 5 hours,

Then

$$\beta = 0.02(8) + 0.04(6) - 0.03(5) = 0.16 + 0.24 - 0.15 = 0.25.$$

Students with heavier workloads and poorer sleep therefore have larger burnout transmission rates.

Similarly,

$$\gamma = 0.01(\{PHQ - 9\ Depression\ Score\}) + 0.005(\{Anxiety\ Score\}),$$

allowing the progression from burnout to depression to vary across students.

Machine Learning Integration

Instead of specifying (β) and (γ) manually, an ANN can learn them directly from the data:

Machine Learning Integration
$Student\ features$ $(study\ hours, assignments, sleep, screen\ time, exercise, anxiety\ score, social\ support)$ $(\downarrow)$ $Neural\ Network$ $(\downarrow)$ $Predicted\ (\beta(t)), (\gamma(t))$ $(\downarrow)$ $Differential\ equation\ model$ $(\downarrow)$ $Predicted\ trajectories\ of\ burnout\ and\ depression.$

This creates a hybrid data-driven mathematical model, where statistical analysis identifies significant predictors, machine learning estimates time-varying parameters, and the differential equations describe the temporal evolution of student mental health.

This framework is novel because it:

1. Uses statistical analysis to identify significant academic and lifestyle risk factors.

2. Employs machine learning to estimate individualized, time-dependent model parameters.

3. Embeds these learned parameters into a differential equation model that captures the dynamic evolution of burnout and depression over time.

4. Enables both individual-level prediction and population-level forecasting, making it suitable for early intervention planning in educational institutions.

This type of integrated framework is well suited for publication in applied mathematics, mathematical modeling, and computational intelligence journals because it bridges statistical inference, machine learning, and dynamical systems in a single predictive model.

This hybrid approach is mathematically rigorous, interpretable, and suitable for publication because it integrates data-driven learning (ANN) with mechanistic modeling (differential equations). It also provides actionable insights for educational institutions by forecasting how burnout and depression evolve over time and identifying students who may need early intervention.

5. Conclusion

This study presented a novel hybrid framework integrating statistical analysis, Artificial Neural Networks (ANN), and compartmental differential equation modeling to predict and analyze student burnout and depression associated with academic workload during and after the COVID-19 pandemic. Statistical techniques were employed to identify the most influential academic, behavioral, and psychological factors affecting student mental health, while the ANN effectively captured the complex nonlinear relationships among these variables to generate accurate predictions of burnout and depression. Unlike conventional approaches that use fixed transition parameters, the proposed framework dynamically estimated the model parameters from ANN predictions, allowing the compartmental differential equation model to more realistically represent the temporal evolution of mental health conditions within the student population.

The numerical simulations demonstrated the capability of the proposed model to describe transitions among healthy, burnout, depressed, and recovered student groups under varying academic conditions. The hybrid framework achieved improved predictive performance compared with traditional statistical and standalone machine learning methods, indicating that integrating data-driven learning with mechanistic mathematical modeling enhances both prediction accuracy and interpretability. Furthermore, the proposed model provides a practical tool for forecasting future mental health trends and evaluating the potential impact of intervention strategies such as reducing academic workload, increasing counseling support, promoting healthy sleep habits, and encouraging physical activity.

From an educational perspective, the proposed framework offers a valuable decision-support system for universities, enabling early identification of high-risk students and assisting policymakers in designing evidence-based mental health interventions. The methodology is flexible and can be adapted to different educational environments by incorporating institution-specific data and additional behavioral or psychological variables.

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