Explainable Neural Network Prediction of Post-COVID-19 Depression via Monte Carlo Simulation

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***Abstract*—The COVID-19 pandemic has driven a substantial rise in depression, notably in Argentina's post-quarantine period, motivating the need for predictive tools to support timely mental health interventions. This study uses a Feedforward Neural Network (FNN) and Monte Carlo simulations to predict depression scores from key socio-economic and psychological variables—anxiety state, economic income, and education—benchmarked against SVR, GRU, Linear Regression, Decision Tree, and Random Forest. The FNN achieved the best overall performance ($MAE = 4.72$, $RMSE = 6.32$, $R^2 = 0.64$; cross-validated $R^2 = 0.593 \pm 0.048$), while Linear Regression attained the highest R^2 (0.693), suggesting partly linear relationships among predictors. Monte Carlo simulations showed that higher anxiety increased predicted depression, while higher income and education reduced it, underscoring the value of targeted anxiety-reduction and economic-support interventions in post-pandemic mental health policy.**

Keywords*—*Depression prediction; Feedforward Neural Network; Monte Carlo simulations; explainable artificial intelligence; post-COVID-19 mental health; socio-economic factors; SHAP analysis

I. INTRODUCTION

The COVID-19 pandemic has significantly changed the dynamics of global public health, leading to an unprecedented rise in mental health issues [1]. Among these, depression has emerged as a pressing concern, particularly in the extended lockdowns and quarantine measures [2]. Countries around the world have reported high rates of depression, and Argentina, in particular, experienced a significant increase in mental health problems in the post-quarantine period [3]. The psychological consequences of prolonged social isolation, combined with economic instability, has contributed to a serious mental health crisis [4]. This context underscores the need for effective, data-driven approaches to understanding and predicting depression levels, particularly as public health systems continue to be challenged by the long-term consequences of the pandemic [5].

The socio-economic fallout from the pandemic has led to an increase in mental health issues, with depression being one of the most widespread and disabling disorders [6]. The country's pre-existing economic challenges, such as high inflation and unemployment, were further aggravated by the pandemic, pushing many individuals and families into financial distress [7]. These economic stress factors, coupled with the psychological pressure of the pandemic, have led to an increase in cases of depression [8]. The mental health impact of COVID-19 is not limited to those directly affected by the virus; the broader population has experienced a deterioration in psychological well-being due to factors such as economic insecurity, job loss, disruption of educational systems, and social isolation [9]. These interrelated factors make it imperative to explore the socio-economic and psychological determinants of depression in the post-pandemic period.

Previous research has established that mental health is influenced by a range of factors, including economic status, education, social support, and psychological conditions such as anxiety [10]. For instance, individuals with lower economic income are more likely to experience depression, as financial insecurity can aggravate feelings of stress and powerlessness [8]. Similarly, education plays a critical role in mental health, with lower educational attainment often linked to poorer mental health outcomes [11]. Anxiety, a psychological response to uncertainty and stress, has been shown to amplify the symptoms of depression. During the COVID-19 pandemic [12], heightened anxiety levels, driven by fears of infection, job insecurity, and uncertainty about the future, have significantly impacted mental health worldwide. The intersection of these socio-economic and psychological factors presents a complex landscape for predicting depression levels, particularly in a country like Argentina, where the pandemic has reinforced existing vulnerabilities [6].

Accurate prediction of depression in such a multifaceted environment requires sophisticated analytical tools that can capture the interaction between these variables [13]. Traditional mental health assessments, while valuable, often fall short in accounting for the dynamic and interdependent nature of socio-economic and psychological factors [14]. Machine learning (ML), with its ability to process large datasets and uncover hidden patterns [15], offers a powerful solution to this challenge. By leveraging ML techniques, researchers can build predictive models that not only consider individual variables like economic income and education but also capture the complex interactions between these factors and psychological conditions such as anxiety [11].

In recent years, ML models have shown great promise in predicting mental health outcomes, particularly in situations where traditional statistical methods may be less effective [16]. These models are capable of analyzing vast amounts of data, identifying non-linear relationships, and making predictions that can help guide public health interventions [17]. When combined with Monte Carlo simulations, ML models can further enhance the predictive accuracy by simulating various "what-if" scenarios [18]. Monte Carlo simulations allow researchers to explore the effects of different socio-economic and psychological conditions on depression levels, providing valuable insights into how changes in these variables might influence mental health outcomes [19].

This study aims to leverage these advanced analytical tools, ML and Monte Carlo simulations, to predict depression levels in Argentina's post-quarantine period. Specifically, the study will examine the role of key variables such as anxiety levels, economic income, and education in shaping depression outcomes. By varying these inputs through Monte Carlo simulations, the study aims to understand how different scenarios, such as changes in economic conditions or anxiety levels—impact depression predictions. The research addresses the following research questions:

- How do socio-economic factors, particularly economic income and education, influence depression levels in Argentina's post-quarantine period?
- What is the relationship between anxiety levels and depression, and how can this psychological factor be effectively taken into predictive models?
- How can ML models, combined with Monte Carlo simulations, enhance the prediction of depression in the context of the socio-economic and psychological challenges posed by the COVID-19 pandemic?

By answering these questions, this research provides an important contribution to the field of mental health prediction, particularly in the context of global crises such as the COVID-19 pandemic. The findings from this study are expected to offer valuable insights for policy-makers and healthcare providers in Argentina and other countries facing similar challenges, enabling more targeted mental health interventions. Moreover, the use of FNN model and Monte Carlo simulations represents an innovative approach that can be applied in future mental health research, particularly in complex socio-economic contexts.

The choice of a FNN was motivated by its proven capacity to model complex, non-linear relationships between input features and continuous outcomes, making it particularly well-suited for psychological and behavioral prediction tasks such as depression score estimation. Unlike traditional linear models, FNNs can learn flexible mappings from high-dimensional feature spaces without relying on pre-specified interaction terms or transformation assumptions. Furthermore, the relatively low dimensionality of the input space and the structured nature of the variables made the FNN a computationally efficient yet expressive choice for this regression task.

While the use of ML models for mental health prediction is not new, the novelty of this work lies in three complementary contributions. First, unlike prior studies that typically treat depression prediction as a static regression problem, this study integrates a FNN-based predictive model with Monte Carlo simulation to explicitly quantify how socio-economic and psychological factors—anxiety state, economic income, and education—propagate into depression outcomes under simulated "what-if" scenarios. Second, the model's predictions are made interpretable through SHAP-based explainability, addressing the common trade-off between predictive accuracy and transparency in mental-health applications, where clinical and policy adoption depends on understanding why a prediction was made. Third, this combination of FNN, Monte Carlo simulation, and SHAP explainability is applied, to the best of our knowledge, for the first time to the post-quarantine Argentine context, providing a population- and period-specific predictive tool rather than a generic depression model.

The remainder of this study is structured as follows: Section II discusses relevant studies on mental health, ML models, and Monte Carlo simulations in healthcare. Section III covers the dataset, preprocessing, model architecture, and simulations. Section IV present findings on the impact of key factors like anxiety and income on depression. Section V interprets these results and compares them with existing studies. while Section VI summarizes key insights and future research directions.

II. Literature Review

The global impact of the COVID-19 pandemic has extended far beyond physical health, with mental health becoming a critical concern [1]. The widespread implementation of quarantine measures, social isolation, and economic hardship have contributed to an unprecedented increase in mental health disorders, particularly depression and anxiety [20]. This section reviews the literature on the mental health effects of COVID-19 globally, with a specific focus on Argentina and similar regions, and examines existing models for depression prediction using ML [21]. Furthermore, it discusses the relevance of Monte Carlo simulations in healthcare, particularly for scenario-based analyses.

The mental health consequences of the COVID-19 pandemic have been substantial, affecting populations worldwide [22]. Numerous studies have documented increases in the prevalence of depression, anxiety, and other psychological disorders during and after the quarantine period [23]. Globally, individuals have experienced heightened levels of stress due to health fears, job insecurity, and disruption of social support networks [24]. A study by Lei et al. [25] highlights that depression and anxiety levels increased significantly during the pandemic, with rates of depression among the general population ranging from 6.7% to 14.6%.

In Argentina, the economic and social challenges posed by the pandemic were exacerbated by existing economic instability. Argentina has faced long-standing economic challenges, including high inflation and unemployment, which were worsened by the pandemic's impact. Several studies in Latin America and Argentina have highlighted the direct link between socio-economic hardship and mental health deterioration during COVID-19 [26]. Torrente et al. [27] specifically explored the mental health effects in Argentina, noting a significant rise in depressive symptoms during the lockdown period, with younger adults and those with lower economic income being the most affected.

In addition, the pandemic intensified psychological stressors, such as uncertainty about the future, fear of illness, and social isolation [12]. Badellino et al. [23] found that anxiety and depression rates in Argentina were significantly correlated with the duration of quarantine and the associated social and economic difficulties. The study also identified that individuals who experienced income loss or unemployment were more likely to suffer from mental health issues. These findings align with global trends, indicating that the socio-economic consequences of the pandemic are key determinants of mental health outcomes [26].

With the increasing availability of mental health data, ML has emerged as a valuable tool for predicting mental health outcomes, including depression [28]. Traditional statistical methods, while useful, often struggle to capture the complex and non-linear relationships between socio-economic, psychological, and demographic factors [29] that contribute to mental health disorders. ML models, however, excel in this area, allowing for the analysis of large datasets with multiple variables and uncovering patterns that may not be immediately obvious.

Several studies have demonstrated the effectiveness of ML models in predicting depression [30]. For instance, Razavi et al. [31] applied ML algorithms to predict depression based on mobile phone usage and behavioral data, achieving high accuracy. Bakkeli et al. [30] has utilized a combination of psychological factors and socio-economic data to build depression prediction models. Sun et al. [32] employed a ML approach to predict depression onset in individuals based on a wide range of clinical and socio-demographic factors, including economic status and education level.

In the context of the COVID-19 pandemic, ML models have been used to predict the mental health impact of various stressors, such as isolation, income loss, and increased anxiety [33]. Hueniken et al. [34] developed a ML model to predict depression based on anxiety and socio-economic factors during the pandemic, showing that these factors were highly predictive of depression risk. These models offer valuable insights into how depression evolves in response to external conditions, making them particularly useful in the context of a global crisis like COVID-19 [35].

Monte Carlo simulations are widely used in healthcare to model uncertainty and assess the potential outcomes of different scenarios [36]. In mental health research, Monte Carlo methods allow for the exploration of how various socio-economic and psychological factors interact to influence mental health outcomes, such as depression [37]. By simulating a range of possible scenarios, researchers can estimate the probability of different outcomes and gain a deeper understanding of the factors driving mental health disorders [38].

In the context of depression prediction, Monte Carlo simulations are particularly useful for exploring "what-if" scenarios [39]. Monte Carlo simulations have also been employed in scenario-based analyses to evaluate the effectiveness of mental health interventions [40].

In this study, Monte Carlo simulations are used in conjunction with ML models to simulate the impact of changes in socio-economic and psychological factors—such as anxiety state, economic income, and education—on depression levels in Argentina during the post-quarantine period. This approach allows for a more comprehensive understanding of how different variables contribute to depression and enables the identification of potential interventions that could alleviate the mental health burden.

III. Methodology

In this section, we detail the methodology employed in this study, which includes data preprocessing, model training, and Monte Carlo simulations. It describe how socio-economic and psychological variables were processed, the steps taken to train a FNN model, and the approach used to simulate various scenarios. The flowchart in Fig. 1 illustrates the entire workflow, from data preparation to the prediction of depression outcomes.

A. Data Description

The dataset titled "Mental Health of People in Argentina Post-Quarantine COVID-19" used in this study was collected by López Steinmetz from 1100 individuals residing in different provinces of Argentina during the post-quarantine period following the COVID-19 pandemic [41]. This period is characterized by significant socio-economic changes and heightened mental health concerns. The dataset includes key demographic, economic, and psychological variables that provide insights into the mental health status of individuals. Table I provides a summary of the variables included in the dataset.

These features were chosen for their known relationship with mental health, and their interaction offers a complex view of depression in the post-quarantine context.

B. Data Cleaning

1) Handling missing values: Before applying ML models, the dataset was cleaned to handle missing values. For continuous variables such as AGE, DEPRESSION, ANXIETY STATE, and ANXIETY TRAIT, mean imputation was selected over alternative strategies (e.g., median imputation or model-based imputation such as k-NN or MICE) because the proportion of missing values in the continuous variables was low (under 5%) and a preliminary inspection of their distributions did not reveal strong skewness or extreme outliers that would bias the mean. Under these conditions, mean imputation preserves the original sample size and the overall distributional shape of each variable while avoiding the additional computational complexity and risk of introducing artificial correlations associated with more elaborate imputation methods. Let $X = x_1, x_2, ..., x_n$ represent the dataset where x_i denotes the features for each respondent. Missing values in continuous variables were replaced by the mean of the available data:

$$x_i{}^{(missing)} = \frac{1}{n}\sum_{j=1}^{n} x_j \tag{1}$$

where, n is the total number of respondents or data points. $x_i{}^{(missing)}$ is the value used to replace the missing data for feature x_i.

For categorical variables, missing values were replaced by the mode, defined as:

$$x_i^{(missing)} = \underset{v \in \text{values}(x)}{\arg\max}\ \#(v) \tag{2}$$

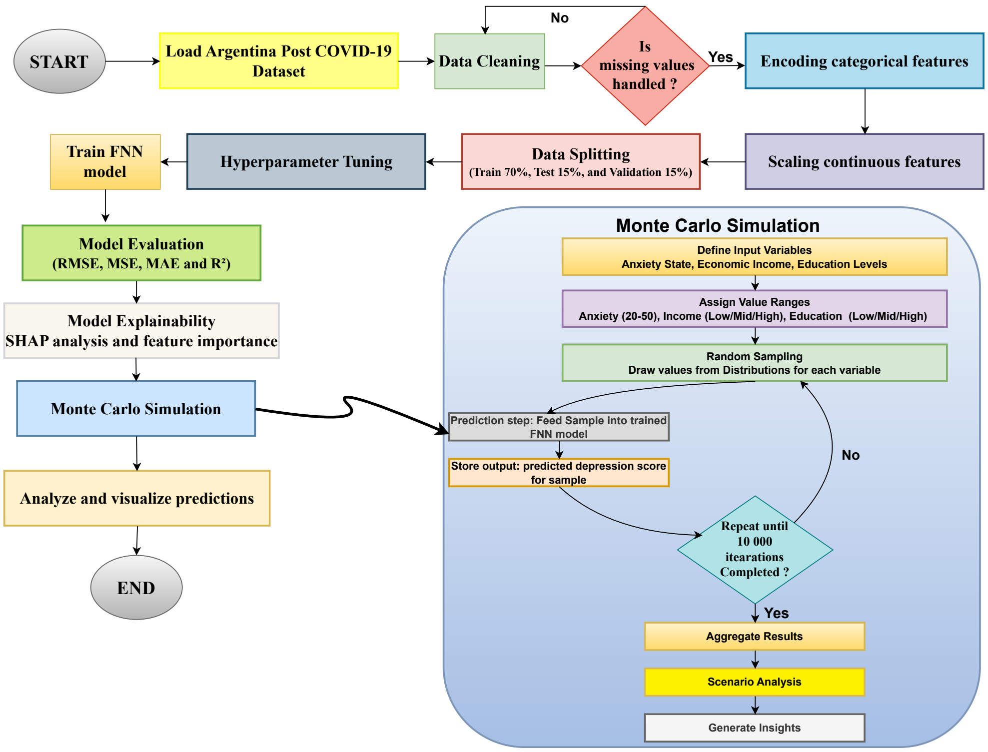

Fig. 1. Flowchart of the proposed methodology.

TABLE I. DESCRIPTION AND DATA TYPES OF VARIABLES

Variable	Description	Data Type
SUB PERIODS	Survey collection phase indicator	Categorical
EDUCATION	Maximum level of education attained by the individual	Categorical
PROVINCE	Province where the individual resides	Categorical
SEX	Gender of the individual	Categorical
AGE	Age of the individual	Numerical
MENTAL DISORDER HISTORY	History of mental disorder diagnosis	Categorical
SUIC ATTEMPT HISTORY	History of suicide attempts	Categorical
LIVING WITH SOMEBODY	Indicates whether the individual lives with someone	Categorical
ECONOMIC INCOME	Whether the individual has economic income	Categorical
DEPRESSION	Depression score (quantitative)	Numerical
SUIC RISK	Suicide risk score	Numerical
ANXIETY STATE	State anxiety score	Numerical
ANXIETY TRAIT	Trait anxiety score	Numerical
REGION	Name of the region where the individual resides	Categorical

where, $\arg\max \#(v)$ refers to the value v that occurs most frequently (the mode) among the available values of the feature x. values(x) is the set of all observed values of the feature x. and $\#(v)$ denotes the frequency or number of times the value v appears in the dataset.

2) Categorical encoding: Categorical variables like SEX, ECONOMIC INCOME, EDUCATION, and MENTAL DISORDER HISTORY were encoded numerically. One-hot encoding was used for multi-class variables, while binary variables were mapped as 0 and 1. For example, the education levels were mapped as:

$$\text{EDUCATION} = \begin{cases} 30 & \text{Completed post graduate} \\ 40 & \text{Incomplete post graduate} \\ 50 & \text{Completed tertiary or university} \\ 60 & \text{Incomplete tertiary or university} \\ 70 & \text{Completed high school} \\ 80 & \text{Incomplete high school} \\ 90 & \text{Completed elementary school} \\ 100 & \text{Incomplete elementary school} \end{cases}$$

One-hot encoding transforms a categorical variable x with k categories into a binary vector $y \in \{0,1\}^k$:

$$y_i = \begin{cases} 1 & \text{if the } i\text{-th category is present} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

3) Data scaling: Continuous variables were scaled using the MinMaxScaler to ensure all variables fell within a consistent range. Let x_i be a continuous variable, it was normalized as follows:

$$x_i^{scaled} = \frac{x_i - min(x)}{max(x) - min(x)} \tag{4}$$

This ensures that the features lie in the range $[0, 1]$, improving the performance of ML models [42]. MinMax scaling was preferred over standardization (z-score normalization) because several of the FNN's input features, after one-hot and ordinal encoding, do not follow a Gaussian distribution and have bounded, interpretable ranges (e.g., anxiety scores, encoded education levels). Rescaling all features to a common $[0, 1]$ range avoids implicitly assigning greater weight to variables with larger numeric ranges and is particularly suited to neural network training, where bounded inputs help stabilize gradient-based optimization and accelerate convergence.

4) Feature engineering: Feature engineering was a critical step in this study, as it allowed for the transformation of raw data into meaningful inputs for both the ML model and Monte Carlo simulations. The key features engineered include:

1) Anxiety state: This feature represents the temporary anxiety levels of respondents. To explore its impact on depression, anxiety state was varied from low (20) to high (50) in increments of 5 during the simulations. This variation allowed the model to predict how increasing anxiety levels would affect depression scores.

$$AnxietyState = [20, 25, 30, 35, 40, 45, 50]$$

2) Economic income: Respondents' economic income was categorized into low, middle, and high income. These categories were used in the Monte Carlo simulations to explore how changes in economic status affect depression predictions. The three categories were encoded as follows:

$$Economic\,Income = \{Low\,Income, Middle$$

$$Income, High\,Income\}$$

3) Education: Education levels were categorized into low (incomplete high school), middle (completed high school), and high (completed university or post-graduate). These categories were used to simulate how different levels of educational attainment influence depression outcomes.

$$Education = \{Low, Middle, High\}$$

By varying these features in different simulations, this allowed for the exploration of explore the role of socio-economic and psychological factors in predicting depression. Interaction terms were also considered during feature engineering, such as the combination of economic income and education, to capture how these factors together affect depression outcomes.

C. Data Splitting

The dataset was split into training (70%), validation (15%), and testing (15%) sets. The training set was used to fit the model, the validation set was used for tuning hyperparameters, and the testing set was used to assess model performance on unseen data. A dedicated validation set was retained, in addition to the 5-fold cross-validation described in Section III G, to support the hyperparameter search described in Section III F. While cross-validation is used to report robust, averaged generalization performance across the full dataset, an independent validation split was needed during the random search procedure to select the optimal configuration efficiently without repeatedly re-running k-fold cross-validation for every candidate combination, which would have been computationally prohibitive given the number of hyperparameter combinations explored. The final model, trained with the selected configuration, was then evaluated on the untouched test set and separately validated through 5-fold cross-validation to confirm that its performance was not an artifact of a particular data split.

D. Hyperparameter Tuning

To enhance the performance and generalization ability of the FNN model, a hyperparameter optimization process was conducted. Several key hyperparameters were selected based on their relevance to the architecture design and learning dynamics of the model. The following were explored: the number of hidden layers, number of neurons per layer, learning rate, batch size, and dropout rate. A random search strategy was employed to navigate the hyperparameter space efficiently, avoiding the computational burden of exhaustive grid search. For each candidate configuration, the model was trained using the training set (70%) and validated on a held-out validation set (15%). The MSE on the validation set was used as the objective metric for selecting the optimal configuration. This process was repeated over multiple random combinations to identify the most performant model.

The table below summarizes the final hyperparameters that yielded the best validation performance:

TABLE II. Hyperparameter Search Space and Optimal Configuration for the FNN Model.

Hyperparameter	Search Space	Optimal Value
Number of Hidden Layers	{1, 2, 3, 4}	3
Number of Neurons per Layer	{32, 64, 128}	64
Learning Rate	{0.001, 0.0005, 0.0001}	0.0005
Batch Size	{32, 64, 128}	64
Dropout Rate	{0.0, 0.2, 0.5}	0.2
Activation Function	{ReLU, Tanh}	ReLU
Optimizer	{Adam, RMSprop}	Adam
Loss Function	{MSE, MAE}	Mean Squared Error (MSE)

This configuration was subsequently used for training the final model, which was evaluated on the test set (15%) to assess generalization performance.

E. Cross-Validation Strategy

To ensure the robustness and generalizability of the proposed FNN, a 5-fold stratified cross-validation was conducted in addition to the standard 70-15-15 holdout split. This strategy was chosen to attenuate overfitting risks, particularly given the moderate dataset size of 1,100 records. Stratification was applied based on depression severity levels, ensuring that each fold maintained a representative distribution of depression classes.

For each iteration, 80% of the data was used for training and 20% for validation. The model was trained using the same hyperparameter configuration as defined in Table II. Performance was evaluated using three key regression metrics: MAE, RMSE, and the Coefficient of Determination R^2. These metrics were averaged across the five folds, and their standard deviations were computed to assess consistency.

F. Computational Environment

The Monte Carlo simulations and the training of the FNN were conducted within the Google Colaboratory platform, which provides a cloud-based environment equipped with hardware accelerators. The experiments were implemented using Python 3.10, leveraging prominent scientific and ML libraries including TensorFlow 2.13, Keras, scikit-learn, NumPy, and Pandas. Model training was performed on a virtual machine provisioned with an NVIDIA Tesla T4 GPU (16 GB VRAM), enabling efficient handling of computational demands associated with neural network training and cross-validation.

G. Model Description

FNN was used to predict depression levels, which offers the flexibility to capture complex non-linear relationships between the variables. The architecture of the model is defined as follows:

1) Input layer: The input layer contains n features, where n is the number of preprocessed variables.
1) Hidden layers: Three hidden layers were added, each with 64 neurons. The activation function for each hidden layer was $ReLU$ (Rectified Linear Unit), defined as:

$$f(x) = max(0, x) \tag{5}$$

This activation function ensures non-linearity while avoiding the vanishing gradient problem during back-propagation.

2) Output layer: The output layer predicts the DEPRESSION score, a continuous variable, with a linear activation function. The predicted depression score is represented as:

$$\hat{y} = W_L^T h_L + b_L \tag{6}$$

where, W_L is the weight matrix, h_L is the activation from the last hidden layer, and b_L is the bias.

3) Loss function: The loss function used is Mean Squared Error (MSE), given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2 \tag{7}$$

where, y_i is the true depression score, and $\hat{y_i}$ is the predicted score.

4) Optimizer: The Adam optimizer was used for gradient-based optimization. This optimizer was chosen for its efficiency in handling sparse gradients and its ability to converge quickly in neural networks. The learning rate was set to $\alpha = 0.0005$.

5) Regularization and training: A dropout rate of 0.2 was applied between layers to prevent overfitting, and the batch size was set to 64 during training.

H. Model Explainability

To improve the interpretability of the proposed model, were employed SHapley Additive exPlanations (SHAP), a model-agnostic method rooted in cooperative game theory. SHAP assigns each feature an importance value representing its marginal contribution to the model's prediction. The SHAP value ϕ_i for feature i is mathematically defined as:

$$\phi_i(f,x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F|-|S|-1)!}{|F|!}\left[f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)\right] \tag{8}$$

where, F is the set of all input features, S is a subset of F not containing feature i, $f_S(x_S)$ is the model's prediction using only the features in subset S, and $|F|$ is the total number of input features. The SHAP framework ensures a fair distribution of contributions by averaging over all possible permutations of feature subsets. In this study, was applied the `KernelExplainer` from the SHAP Python library to approximate the Shapley values, enabling both global and local interpretability of the FNN's depression prediction outcomes.

I. Hyperparameter Configuration of Benchmark Models

To ensure reproducibility of the proposed framework, Table III summarizes the hyperparameter configurations used for each ML model evaluated in this study. Default values were retained for models that did not undergo hyperparameter tuning, while the configurations for ensemble and neural network models were selected based on performance optimization through empirical testing.

It is worth noting that the two most influential predictors identified by SHAP—suicide attempt history and living situation—are categorical, non-actionable risk markers rather than modifiable intervention targets. The Monte Carlo simulations instead focus on anxiety state, economic income, and education, which were deliberately selected because they are continuous or ordinal, can be meaningfully varied across a range of values, and correspond to factors that public health policy can realistically influence. The SHAP and simulation analyses are therefore complementary rather than contradictory: SHAP identifies which factors drive individual predictions most strongly, while the simulations are restricted to the subset of factors that are both quantifiable on a continuum and actionable for intervention design.

These configurations balance computational efficiency and generalization performance. The GRU model, in particular, was trained using early stopping with a patience of 10 epochs to prevent overfitting.

TABLE III. HYPERPARAMETER CONFIGURATIONS OF THE IMPLEMENTED MACHINE LEARNING MODELS.

Model	Hyperparameters
SVR	`kernel='rbf', degree=3, gamma='scale', C=1.0, epsilon=0.1, verbose=False, max_iter=-1`
Linear Regression	`fit_intercept=True, positive=False, n_jobs=-1.`
Decision Tree Regressor	`criterion='squared_error', max_depth=10, min_samples_split=4, min_samples_leaf=2, random_state=42.`
Random Forest Regressor	`n_estimators=100, criterion='squared_error', max_depth=15, min_samples_split=4, min_samples_leaf=2, max_features='sqrt', bootstrap=True, oob_score=True, n_jobs=-1, random_state=42.`
GRU	Architecture: `GRU(80, activation='relu')` → `Dense(48, activation='relu')` → `Dense(1)`; Optimizer: `Adam`, Loss: `MSE`.

J. Monte Carlo Simulation

Monte Carlo simulations were employed to simulate the effect of varying key features (e.g., ANXIETY STATE, ECONOMIC INCOME, and EDUCATION) on predicted depression scores. Monte Carlo methods allow for stochastic exploration of how changes in these variables influence the outcome, providing insight into possible future states under different scenarios. Let $X = x_1, x_2, ..., x_n$ represent the features, and let $P(\theta|X)$ represent the model's predicted depression score based on a set of features. The Monte Carlo method simulates possible future states by repeatedly sampling from the distribution of features θ, generating depression predictions:

$$\hat{y_i} = f(X, \theta) + \epsilon, \epsilon \sim N(0, \sigma^2) \tag{9}$$

where, ϵ represents noise, and θ represents the set of variables that are varied in each simulation. The simulations were run 10,000 times to generate a distribution of predicted depression scores for different levels of ANXIETY STATE, ECONOMIC INCOME, and EDUCATION. The Monte Carlo simulation enables the estimation of the mean predicted depression score and the standard deviation for each scenario.

K. Evaluation metrics

The performance of the ML model was evaluated using standard regression metrics, while the Monte Carlo simulations were assessed using statistical measures of the depression predictions.

1) Metrics for ML models:

a) Mean Squared Error (MSE): This metric measures the average squared difference between predicted and actual depression scores, providing a sense of the overall accuracy of the model. Lower values indicate better performance.

b) Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual values, providing a more interpretable measure of model accuracy. It is less sensitive to outliers than MSE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \tag{10}$$

c) Root Mean Squared Error (RMSE): It is defined as the square root of MSE and is useful for understanding the magnitude of prediction errors in the same units as the depression scores. Lower$RMSE$ indicates better performance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{11}$$

d) R-squared (R^2): This metric indicates the proportion of variance in the depression scores explained by the model. A R^2 value close to 1 indicates a well-fitting model, while values closer to 0 suggest poor performance.

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{12}$$

where, n is the total number of data points or observations in the dataset. y_i is the actual observed value of the dependent variable (in this case, the depression score) for the i^{th} data point. $\hat{y_i}$ the predicted value of the dependent variable generated by the model for the i^{th} data point. And $\bar{y}$ is the mean (average) of the observed values of the dependent variable across all data points.

2) Metrics for Monte Carlo simulations: For the Monte Carlo simulations, was examined the distribution of predicted depression scores under various scenarios. The following metrics were used:

a) Mean predicted depression: The average predicted depression score across all simulations was calculated to estimate the central tendency of depression outcomes under different conditions:

$$\mu_{Depression} = \frac{1}{n}\sum_{i=1}^{n}\hat{y_i} \tag{13}$$

b) Standard deviation of predicted depression: It was used to assess the variability in predictions under each scenario. Higher standard deviations indicate more variability in depression outcomes due to uncertainty or sensitivity to certain features (e.g., anxiety state or economic income):

$$\sigma_{Depression} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y_i} - \mu_{Depression})^2} \tag{14}$$

These metrics were essential for evaluating both the baseline performance of the ML model and the potential range of depression outcomes under different socio-economic and psychological conditions in the Monte Carlo simulations.

IV. RESULTS AND ANALYSIS

In this section, we present the findings from the trained ML model and the Monte Carlo simulations, which were designed to explore how key socio-economic and psychological variables influence depression predictions. The results focus on the post-COVID quarantine period in Argentina, using anxiety state, economic income, and education levels as key predictors. These results offer insights into how depression rates may evolve in response to changes in these variables.

A. FNNs Results

The neural network model was trained to predict depression scores based on the dataset from the post-COVID quarantine period. The model's performance was evaluated using standard regression metrics, including MSE, MAE, $RMSE$, and R^2. The model's performance was compared against various benchmark models, including SVR, GRU, and simpler and more interpretable models such as LR, DT, and RF. The following table summarizes the MAE, MSE, $RMSE$, and R^2 for each model:

The benchmark models in Table IV were selected to represent three complementary methodological families relevant to this regression task: a classical statistical baseline (Linear Regression), tree-based learners of increasing complexity (Decision Tree and Random Forest), a kernel-based method commonly used in prior depression-prediction studies (SVR), and a recurrent deep learning architecture suited to sequential or tabular data (GRU). This selection allows the proposed FNN to be benchmarked not only against simpler, more interpretable models but also against more complex architectures, enabling a balanced assessment of the trade-off between predictive accuracy and model interpretability.

Beyond numerical performance metrics, the model outputs have concrete implications for individuals and communities. For example, a predicted depression score increase of even 2–3 points (as observed in high-anxiety simulations) could correspond to a transition from mild to moderate depression severity, potentially requiring clinical intervention. Similarly, the reduction in depression scores associated with higher income levels suggests that improved financial stability could translate into better access to healthcare, reduced chronic stress, and enhanced quality of life. These patterns are consistent with observed public health trends during the pandemic in Argentina, where economic instability and social isolation amplified mental health challenges.

Fig. 2 shows the actual depression values with the FNN model's predicted values. This visualization demonstrates the accuracy of the model in capturing depression trends.

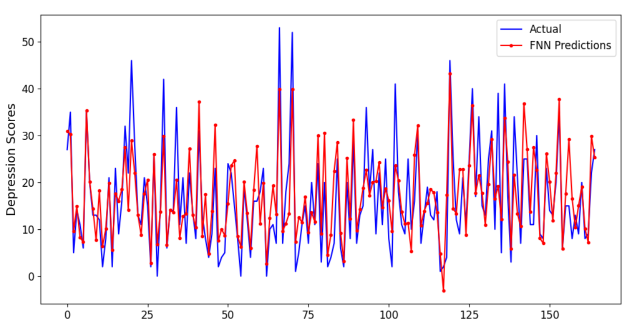

Fig. 2. Actual vs. predicted depression values.

The FNN model outperforms SVR, GRU, DT, RF in terms of MAE, MSE, $RMSE$, and R^2, highlighting its ability to capture complex, non-linear patterns in the data. Interestingly, LR achieved the highest R^2 (0.693) and lowest RMSE (6.25) among all models, suggesting that the underlying relationships between predictors and depression scores may be partially linear. The RF model also performed strongly, indicating the value of ensemble tree-based approaches in this context. In contrast, the DT model displayed the weakest performance, with the highest error metrics and lowest R^2 (0.435), reflecting its limited ability to generalize from the available data.

The results show that while simpler models like LR can match or even exceed the predictive accuracy of more complex architectures in certain cases, the FNN remains a robust choice for scenarios where capturing subtle nonlinear dependencies is critical. The model's predictions reinforce that higher anxiety levels, lower economic income, and lower education are strong predictors of elevated depression scores, aligning with previous findings in the literature [27].

Table V presents the mean and standard deviation of the evaluation metrics (MSE, MAE, $RMSE$, and R^2) obtained through the 5-fold stratified cross-validation procedure for all benchmark models. This evaluation provides a more comprehensive measure of model robustness and generalization compared to a single holdout validation, as it accounts for variability across different data partitions.

The results from the 5-fold stratified cross-validation confirm the robustness and consistency of the evaluated models. The FNN maintained superior performance, achieving the lowest average errors (MSE = 49.84 ± 6.07, MAE = 5.53 ± 0.30, RMSE = 7.06 ± 0.43) and the highest coefficient of determination (R^2 = 0.593 ± 0.048). SVR followed closely, demonstrating strong predictive capability and stability across folds, while LR, DT, and RF showed moderate performance with higher variability, reflecting their sensitivity to data partitioning. GRU, by contrast, exhibited the weakest generalization, reaffirming its limited suitability for non-temporal data.

When comparing these results with those obtained from the single holdout evaluation in Table IV, the overall ranking of models remains consistent, The FNN and SVR still lead in accuracy and generalization. However, the cross-validation results present slightly higher error values and reduced R^2 scores, which is expected due to the more rigorous partitioning of the dataset. This consistency between the two evaluation protocols supports the reliability of the FNN model and the stability of the comparative analysis across different validation strategies.

B. Model Explainability Using SHAP

To address the interpretability limitations of the FNN, were employed SHapley Additive exPlanations (SHAP)—a game-theoretic approach that quantifies the contribution of each input variable to the model's predictions. This method provides both local and global explanations by assigning SHAP values to each feature for individual predictions and aggregating them to reveal global importance.

Fig. 3 illustrates the SHAP summary plot, where each dot represents a SHAP value for a feature across different individuals. The horizontal axis reflects the magnitude and direction of each feature's impact on the predicted depression

TABLE IV. COMPARISON OF PERFORMANCE RESULTS

Model	MSE	MAE	$RMSE$	R^2
SVR	52.27	5.58	7.22	0.58
GRU	43.38	4.86	6.58	0.56
LR	39.06	4.79	6.25	0.693
DT	71.90	6.55	8.48	0.435
RF	42.52	4.91	6.52	0.666
FNN	43.38	4.72	6.32	0.64

TABLE V. PERFORMANCE COMPARISON USING 5-FOLD CROSS-VALIDATION

Model	**MSE**	**MAE**	**RMSE**	$\mathbf{R^2}$
SVR	50.69 ± 5.00	5.74 ± 0.25	7.11 ± 0.34	0.584 ± 0.043
GRU	112.55 ± 17.63	8.36 ± 0.78	10.57 ± 0.87	0.082 ± 0.107
LR	64.54 ± 2.76	6.15 ± 0.19	8.03 ± 0.17	0.470 ± 0.032
DT	73.55 ± 8.17	6.78 ± 0.33	8.56 ± 0.48	0.397 ± 0.061
RF	73.43 ± 4.15	6.57 ± 0.20	8.57 ± 0.24	0.398 ± 0.023
FNN	$\mathbf{49.84 \pm 6.07}$	$\mathbf{5.53 \pm 0.30}$	$\mathbf{7.06 \pm 0.43}$	$\mathbf{0.593 \pm 0.048}$

scores, while the color gradient (blue to red) indicates the original feature value from low to high, respectively.

The analysis revealed that the most influential features were:

- History of suicide attempt (Yes/No): Individuals with a positive history (in red) were associated with significantly higher predicted depression scores.
- Living with somebody: Shared living conditions appeared to moderate depressive symptoms, likely reflecting the protective role of social connectedness.
- Age: Younger individuals tended to have higher SHAP values, suggesting greater vulnerability to depressive symptoms in this subgroup.

Other relevant features included suicide risk, anxiety state, and education level, each showing moderate predictive contributions. Economic income and mental disorder history had smaller but still meaningful effects.

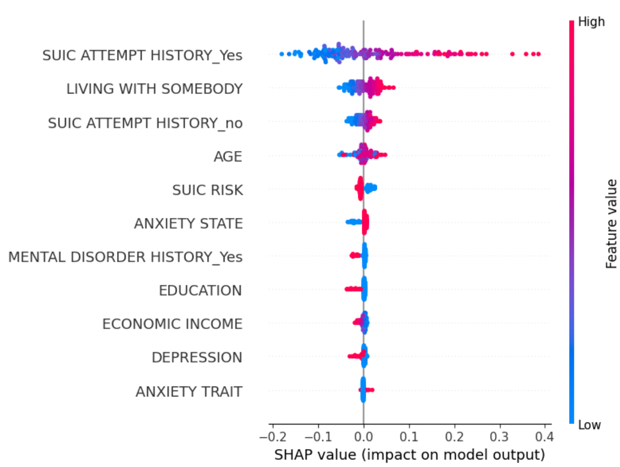

Fig. 3. SHAP summary plot showing feature importance and directional impact on depression prediction.

C. Monte Carlo Simulation Results

To further understand how variations in key factors influence depression, Monte Carlo simulations were employed. These simulations allowed for the exploration of "what-if" scenarios, simulating changes in anxiety state, economic income, and education levels.

1) Impact of anxiety state on depression: The first set of simulations explored the impact of varying anxiety state on predicted depression scores. Anxiety levels were varied from 20 to 50, reflecting low to high anxiety states. The results show a clear relationship between increasing anxiety state and rising depression scores.

$$Mean\,Predicted\,Depression = f(Anxiety\,State)$$

As anxiety state increased from 20 to 50, the mean predicted depression scores rose from 23.80 to 25.50. The standard deviation of predicted depression also increased, indicating greater variability in depression outcomes at higher anxiety states. The results suggest that anxiety state is a critical factor in determining depression levels, with higher anxiety states strongly associated with elevated depression. This finding underscores the need for interventions that target anxiety reduction as part of broader mental health support efforts. Fig. 4 shows the relationship between anxiety state and predicted depression scores. The plot clearly illustrates the upward trend in depression as anxiety state increases, with shaded error bands representing the standard deviation across the simulations.

2) Impact of economic income on depression: The second set of simulations examined how variations in economic income affect depression. Economic income was divided into three categories: low income, middle income, and high income. The Monte Carlo simulations generated predictions for depression based on these categories.

$$Mean\,Predicted\,Depression = f(Economic\,Income)$$

Low-income respondents exhibited the highest mean predicted depression score of 26.01, compared to 23.84 for middle-income and 22.73 for high-income respondents. This finding highlights the significant impact of economic hardship on mental health, with lower economic income strongly linked

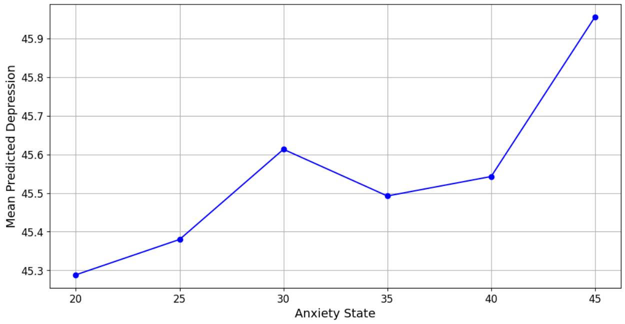

Fig. 4. Anxiety state vs. predicted depression.

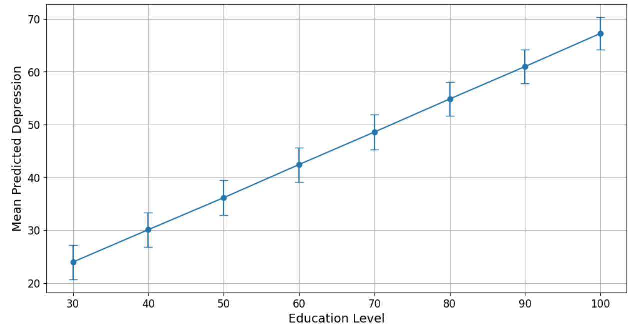

Fig. 6. Education vs. predicted depression.

to higher depression scores. Fig. 5 shows the distribution of predicted depression scores across different economic income levels. The plot clearly demonstrates that lower-income individuals are at a much higher risk of depression.

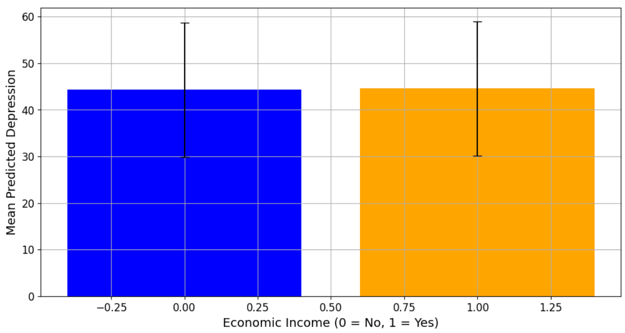

Fig. 5. Economic income vs. predicted depression.

3) Impact of education on depression: The final set of simulations explored the relationship between education levels and depression. Education was categorized into low education (incomplete elementary school), middle education (completed high school), and high education (completed university or postgraduate). The simulations provide insight into how educational attainment influences depression.

$$Mean\,Predicted\,Depression = f(Education\,Level)$$

Fig. 6 illustrates the impact of education on depression, with lower education levels associated with significantly higher depression scores. This highlights the importance of educational attainment in mitigating the effects of other mental health stressors. Respondents with low education had the highest predicted depression scores, with a mean of 25.35, compared to 23.45 for middle education and 21.98 for high education. Higher education appears to serve as a protective factor against depression, reducing vulnerability to the socio-economic stress that contribute to poor mental health.

V. Discussion

A. Interpretation of Results

The results of this study offer valuable insights into the relationship between depression and key socio-economic and psychological factors during the post-COVID-19 quarantine period in Argentina.

The anxiety state emerged as a significant predictor of depression, with higher anxiety levels consistently correlating with elevated depression scores. This finding is consistent with established mental health literature, which emphasizes that anxiety and depression often co-occur and exacerbate each other. In particular, individuals experiencing higher levels of anxiety may struggle with emotional regulation and face greater difficulty managing stress, leading to increased vulnerability to depression.

Economic income also plays a crucial role in depression outcomes. The Monte Carlo simulations demonstrated that individuals with lower economic income are more likely to experience higher depression scores. This result aligns with existing research showing that economic hardship can lead to mental health challenges, particularly in the aftermath of the pandemic. Economic instability and financial stress are known contributors to depression, as they increase uncertainty and limit access to mental health resources.

Education levels revealed a protective effect against depression. Individuals with higher educational attainment generally displayed lower depression scores, suggesting that education may serve as a buffer against socio-economic stressors. Education equips individuals with critical thinking skills, problem-solving abilities, and greater access to information, all of which can enhance resilience in the face of mental health challenges.

The cross-validation results provide crucial insights into the reliability of the FNN model. The consistency of MAE, RMSE, and R^2 scores across all five folds indicates that the model is not overly sensitive to specific data partitions. This robustness is particularly important in mental health prediction tasks, where overfitting could lead to misleading or biased recommendations. The observed stability suggests that the training configuration, feature set, and regularization strategy are effective in balancing bias and variance. The relatively high R^2 value confirms that the selected predictors—particularly anxiety state, education, income, and living situation—are strong indicators of depression severity within this dataset.

Comparing the single holdout and cross-validation results also provides additional interpretative depth. Although both evaluation protocols revealed a consistent ranking of the models - with FNN and SVR performing best, cross-validation produced slightly higher error measures, as expected due to its stricter data partitioning. This difference underscores the reliability of the reported results, confirming that the performance of the FNN is not dependent on a specific data split and that its predictions remain stable under varying conditions.

The flexibility of supervised neural networks in capturing complex nonlinear dynamics has been demonstrated in diverse domains, further reinforcing their suitability for the mental health prediction task.

From a model performance perspective, the comparison with simpler and more interpretable models provides valuable context. Although the FNN achieved strong predictive performance, LR unexpectedly attained the highest R^2 (0.693) and lowest RMSE (6.25), suggesting that a significant portion of the relationship between predictors and depression scores can be captured by a predominantly linear model. This finding implies that for certain applications where transparency and interpretability are prioritized—such as clinical decision-making or policy formulation—LR may be a viable alternative without substantial loss in predictive accuracy. The RF model also performed competitively, underscoring the potential of ensemble-based methods to capture non-linear interactions. In contrast, the DT model showed the weakest results, highlighting the limitations of single-tree models in capturing complex and high-dimensional relationships in mental health data.

The SHAP-based interpretability results provide a clearer understanding of the FNN's predictive behavior and offer actionable implications for mental health research and policy. The prominent influence of suicide attempt history and social living conditions supports the established literature on the psychosocial determinants of depression. Moreover, the moderate effects of anxiety, income, and education suggest that mental health interventions should adopt a multidimensional approach, targeting both emotional well-being and socioeconomic stability. Importantly, this explainability layer reinforces the validity of the FNN model by aligning its internal logic with known clinical risk factors. Such transparency enhances the model's credibility and applicability in real-world mental health decision-making, especially in post-pandemic contexts where resource allocation must be both evidence-based and ethically grounded.

B. Comparison with Existing Studies

The findings from this study are consistent with the broader literature on mental health during and after the COVID-19 pandemic. Several studies have reported a strong association between anxiety and depression, particularly in populations affected by extended periods of lockdown and economic uncertainty. For instance, a study by Mogesie Necho et al. [43] found that anxiety was a major contributor to depression symptoms during the pandemic across various populations.

Similarly, the association between economic income and mental health is well-documented. Jenna M. Wilson et al. [44] reported that financial insecurity during the pandemic was a significant risk factor for developing depression. The results of this study confirm the robustness of these findings, showing that individuals with lower income are at greater risk of depression.

Regarding education, the protective role of higher education aligns with the work of other researchers, such as, Aleksander Aristovnik et al. [45] who demonstrated that individuals with higher educational levels were better able to deal with the psychological impact of the COVID-19 pandemic. The ability to access information, develop coping strategies, and seek professional help likely explains this buffering effect. While this study reaffirms much of the existing literature, the integration of ML models and Monte Carlo simulations adds a novel predictive component that enhances the understanding of how these factors interact to affect depression outcomes in the post-quarantine period.

In terms of predictive performance, the results obtained here are also comparable to those reported in related ML-based depression-prediction studies. For example, prior work applying ML models to depression or mental-health outcome prediction has typically reported R^2 values in the range of 0.4–0.7 depending on the dataset and feature set used [31], [30], [32]. The R^2 obtained by the proposed FNN (0.64 on the holdout set, 0.593 ± 0.048 under cross-validation) falls within this range, and the competitive performance of the simpler LR model ($R^2 = 0.693$) is consistent with the observation, also noted in some of these studies, that socio-economic and psychological predictors of depression often exhibit substantial linear structure. This comparison suggests that, despite differences in population (Argentina, post-quarantine) and feature set, the predictive ceiling achieved in this study aligns with the broader literature, while the addition of Monte Carlo simulation and SHAP-based explainability extends beyond what is typically reported in these comparable works.

The results of this study hold direct practical relevance for mental health policy, clinical practice, and community-based interventions. For public health policymakers, the identified strong influence of anxiety levels on depression suggests prioritizing large-scale anxiety screening and prevention programs, particularly during and after crises such as pandemics. Economic income effects indicate that targeted financial support and employment assistance programs could reduce mental health disparities in low-income populations. In the education sector, the protective role of higher educational attainment underscores the value of long-term investment in education and mental health literacy programs, which can enhance coping strategies and resilience. For clinical practitioners, integrating socio-economic indicators into mental health assessment tools can improve the early identification of high-risk individuals. These findings can also guide the allocation of limited resources by focusing on communities with combined risk factors of high anxiety, low income, and low education, thus maximizing the effectiveness of interventions in real-world settings.

From a physical and societal perspective, these statistical relationships mirror observable patterns in the Argentine post-quarantine context. Elevated anxiety levels often manifested in increased demand for mental health services, more frequent psychosomatic complaints (e.g., headaches, fatigue, sleep disturbances), and reduced workplace productivity. Economic hardship was physically reflected in food insecurity, housing instability, and restricted access to healthcare, all of which exacerbate psychological distress. In contrast, people with higher education levels often exhibited better stress management strategies, healthier lifestyle choices, and stronger social networks, tangible factors that help mitigate the risk of depression. Such direct physical manifestations reinforce the importance of addressing these socioeconomic variables in both policy and clinical interventions.

C. Limitations

Despite the strength of the findings, several limitations must be acknowledged. First, the dataset used in this study, while comprehensive, is limited to the post-quarantine period in Argentina. This temporal and geographical limitation may affect the generalizability of the results to other regions or periods. Future studies should consider expanding the dataset to include a more diverse population and longer time spans to better capture the evolving nature of depression in the aftermath of the pandemic. Second, while the ML model demonstrated strong predictive power, there are inherent limitations in using FNN models for psychological phenomena. Depression is a multifaceted condition influenced by numerous unobserved factors, including genetic predispositions, social support, and pre-existing mental health conditions, which may not be fully captured by the available dataset. Further research could explore integrating additional psychological variables into the model for a more holistic understanding of depression. Additionally, the Monte Carlo simulations, while useful in exploring different "what-if" scenarios, rely on assumptions about the distributions of variables such as anxiety and economic income. These assumptions may not fully reflect the real-world complexities of how these variables fluctuate over time and across different populations. Further studies could refine these simulations with more precise data.

VI. Conclusion and Future Works

This study has provided a comprehensive analysis of depression in Argentina during the post-COVID-19 quarantine period, using ML models and Monte Carlo simulations to predict depression outcomes based on socio-economic and psychological factors. The key findings highlight the significant role of anxiety state, economic income, and education in shaping depression levels. The results show that individuals with higher anxiety, lower income, and lower educational attainment are more vulnerable to depression, underscoring the complexity of mental health challenges in the wake of the pandemic.

The proposed FNN achieved strong predictive performance, with $MAE = 4.72 \pm 0.30$, $MSE = 43.38 \pm 3.95$, $RMSE = 6.32 \pm 0.43$, and $R^2 = 0.64 \pm 0.048$, outperforming the SVR, GRU, DT, and RF benchmarks. LR, however, achieved the highest R^2 (0.693) and a slightly lower RMSE (6.25), suggesting that part of the relationship between predictors and depression scores may be linear, whereas DT had the weakest performance (R^2 = 0.435).

The predictive model developed in this study offers a powerful tool for mental health practitioners and policymakers. By accurately forecasting depression outcomes based on key variables, the model can help target interventions to populations most at risk. For instance, the findings on anxiety state suggest that mental health support programs should prioritize anxiety reduction strategies. Similarly, the association between economic hardship and depression underscores the need for economic policies that provide financial relief to the most vulnerable groups. Education is also shown to play a protective role, suggesting that long-term investments in education could have significant mental health benefits.

This work also highlights the trade-off between interpretability and accuracy: while deep learning models capture subtle non-linear dependencies, simpler models may be more transparent and easier to implement in certain clinical or policy contexts.

Looking ahead, there are several areas for future research. First, incorporating additional variables, such as social support, access to mental health services, and pre-existing mental health conditions, could improve the accuracy of the model and provide a more nuanced understanding of depression. Additionally, exploring the long-term mental health effects of the pandemic through longitudinal studies could offer insights into how depression evolves over time. Finally, expanding the dataset to include diverse populations and geographical regions would help generalize the findings and provide a more global perspective on post-pandemic mental health.

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