Original article

Analysis of depression in El Salvador using machine learning models

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Análisis de la depresión en El Salvador mediante modelos de aprendizaje automático

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Abstract
Introduction. Depression is a frequent mental disorder and one of the leading causes of disability worldwide. It has a multifactorial origin, resulting from the interaction between biological, psychological, social, and structural factors. **Objective.** Analyze the factors associated with depression in adults and older adults in El Salvador. **Methodology.** A cross-sectional analytical study with a predictive approach was conducted on 7249 participants. A machine learning–enhanced logistic regression model was applied, trained on 80 % of the data and evaluated on 20 %, optimized through cross-validation and Monte Carlo simulations. The risk profile was categorized using clustering analysis. **Results.** Depression was associated with anxiety OR 10.385; (95% CI 8.760–12.310), post-traumatic stress disorder (OR 4.471; 95% CI: 3.257–6.138), COVID-19-related stress OR 2.42; (95% CI 1.437–4.092), suicidal ideation OR 1.968; (95% CI 3.257– 6.13), recent discrimination OR 1.338; (95% CI 1.090–1.643), being female OR 1.291; (95% CI 1.072–1.55), unmet basic needs OR 1.192; (95% CI 1.016–1.399), and functional disability OR 1.044; (95% CI 1.038–1.051). The average AUC was 0.836. Clustering analysis identified three groups: high, medium, and low risk. The high-risk group had low social integration and high functional and emotional impairment. The departments of Morazán and Chalatenango had the highest proportion of high risk. **Conclusion.** Depression is influenced by a complex interaction of emotional, social, and structural factors, with a higher prevalence in women and differences in the geographical distribution of risk, which requires comprehensive and targeted interventions.

Keywords
Depression, Artificial Intelligence, Machine Learning, Cluster Analysis, Risk Factors, Mental Health.

Resumen
Introducción. La depresión es un trastorno mental frecuente y una de las principales causas de discapacidad a nivel mundial. Presenta un origen multifactorial, derivado de la interacción de factores biológicos, psicológicos, sociales y estructurales. **Objetivo.** Analizar los factores asociados a la depresión en adultos y personas mayores de El Salvador. **Metodología.** Se realizó un estudio transversal analítico con enfoque predictivo en 7249 participantes. Se aplicó un modelo de regresión logística basado en modelos de aprendizaje automático conocido en inglés como *machine learning*, entrenado con el 80 % de los datos y evaluado con el 20 %, optimizado mediante validación cruzada y simulaciones de Monte Carlo. El perfil de riesgo se categorizó mediante análisis de conglomerado. **Resultados.** La depresión mostró una asociación significativa con ansiedad (OR 10,385 IC 95 % 8,760-12,310), trastorno de estrés postraumático OR 4,471 (IC 95 % 3,257-6,138), estrés por COVID-19 OR 2,42 (IC 95 % 1,437-4,092), ideación suicida OR 1,968 (IC 95 % 1,605-2,414), discriminación reciente OR 1,338 (IC 95 % 1,090-1,643), sexo femenino OR 1,291 (IC 95 % 1,072-1,553), necesidades básicas insatisfechas OR 1,192 (IC 95 % 1,016-1,399) y discapacidad funcional OR 1,044 (IC 95 % 1,038-1,051). El promedio del área bajo la curva fue de 0,836. El análisis de conglomerado identificó tres grupos diferenciados según nivel de riesgo: alto, medio y bajo. El grupo de alto riesgo presentó baja integración social y elevada afectación funcional y emocional, concentrándose principalmente en los departamentos de Morazán y Chalatenango. **Conclusión.** La depresión resulta de una interacción compleja de factores emocionales, sociales y estructurales, con mayor prevalencia en mujeres y variaciones geográficas del riesgo, lo que exige intervenciones integrales y focalizadas.

Palabras clave
Inteligencia Artificial, Aprendizaje Automático, Análisis por Conglomerados, Factores de Riesgo, Salud Mental.

Introduction

Depression is a frequent mental disorder and a major public health issue, affecting millions of people around the world.[1] According to the World Health Organization (WHO), depression is the leading cause of health-related disability globally and constitutes a significant global burden of disease.[2]

It is estimated that more than 5 % of the adult population suffers from depression, with approximately 300 million people affected each year[3]. These figures have seen a steady increase in recent decades, with sharp rises during global crises such as the COVID-19 pandemic.[4,5]

Depression manifests itself through a combination of emotional, cognitive, and physical symptoms, including persistently low mood, loss of interest or pleasure in activities, negative thoughts, sleep and appetite disturbances, lack of energy, and difficulty concentrating.[6] These symptoms not only affect people's ability to perform their daily activities, but also have a profound impact on their quality of life and overall well-being.[7]

Depression is a multifactorial condition, involving biological, psychological, and social factors, thus emphasising the intricacy of the problem.[8] Factors such as genetic predisposition, neurochemical imbalances, traumatic experiences, chronic stress, poverty, and discrimination play a crucial role in its onset.[7] In addition, sociocultural contexts and structural inequalities increase vulnerability in certain population groups, increasing the need for specific interventions.[9]

In El Salvador, data from the 2022 National Mental Health Survey (NMHS) showed a high burden of depressive symptoms, with 22.1 % of adults and 25 % of older adults reporting some degree of depression.[10] This situation reinforces the urgency of investigating the factors associated with depression in order to develop more effective prevention strategies, improve access to timely treatment, and promote environments conducive to mental health.[11] Understanding these factors not only contributes to policy design but also improves access to effective treatment and encourages the creation of environments that promote mental health.

In this context, the use of advanced data analysis tools, such as artificial intelligence (AI) models, has become increasingly relevant in mental health.[12] These technologies enable processing large volumes of data, identifying complex patterns, and generating highly accurate predictive models.[13] The application of techniques such as machine learning models facilitates the detection of factors associated with depression, improves risk classification, and supports clinical and public health decision-making.[13] Integrating AI approaches into the analysis of the NMHS contributes to a deeper, more objective, and personalized understanding of the determinants of mental health in the Salvadoran population. Therefore, the objective of this research is to analyze the factors associated with depression in adults and older adults in El Salvador using machine learning models.

Methodology

A cross-sectional analytical study with a predictive approach was conducted using data from the NMHS 2022. This survey was developed by the Ministry of Health, through the National Institute of Health of El Salvador, to generate nationally representative information on mental health problems among people aged three years and older. The scope of this research was limited to the analysis of data that had been previously processed, validated, and made official at the national level.

The instruments used by NMHS 2022 included the Posttraumatic Stress Disorder Checklist-5 (PCL-5) to assess posttraumatic stress disorder, the Perceived Community Support Scale to measure community integration and participation, and the Discrimination Scale to quantify perceived discrimination. Functional disabilities were assessed using the World Health Organization Disability Assessment Schedule 2.0 (WHODAS 2.0).

The Generalized Anxiety Disorder-7 (GAD-7) was used to assess generalized anxiety, and the Patient Health Questionnaire-9 (PHQ-9) was used to measure the severity of depression. Both variables were dichotomized based on the presence of at least some degree of anxiety or depression. The risk of alcohol, tobacco, and other substance use was classified using the WHO Alcohol, Smoking, and Substance Involvement Screening Test (ASSIST). Perceived stress was assessed using the 10-question Perceived Stress Scale (PSS-10) with a total score ranging from zero to 40. The score was classified into five ordinal levels that included no stress (0), very low stress (1-6), low stress (7-13), moderate stress (14-26), and high stress (27-40). Resilience was assessed using the Brief Resilience Scale (BRS); suicidal ideation and suicidal behavior were assessed using the Suicide Risk Scale (ERS).

The instruments used for data collection were reviewed and validated by professionals in psychology and psychiatry. The staff who collected the data were previously trained; data collection took place between August and November 2022 and involved 11 269 people.[10] For the analysis, individuals over the age of 18 were included, and cases with incomplete information were excluded. The initial database included 7516 records, of which 7249 were considered valid for analysis.

Living conditions were assessed using the Unsatisfied Basic Needs (UBN) method, used in Latin American countries to measure deprivation at the individual and household levels.[14] This method classifies as UBN those individuals or households that have at least one of the following deprivations: access to adequate housing, access to health services, access to education, or economic capacity.

The housing component of the UBN method included housing quality and overcrowding. Housing was considered inadequate when it had dirt floors or walls, roofs made of natural fibers such as straw or palm, or the use of waste materials. Overcrowding was defined as three or more people living in the same room.

Also, as part of the UBN method, access to sanitation services was assessed based on the type of excreta disposal system and the availability of basic services. Access to education was measured by school-age children's attendance at educational institutions. Economic capacity was analyzed based on the probability of insufficient income, taking into account the age, educational level, household size, and employment status of household members.

In the statistical analysis, continuous variables were evaluated using the Anderson-Darling normality test. Due to a non-normal distribution of the data, ($p < 0.05$), the median was used as a measure of central tendency and the interquartile range as a measure of dispersion. For categorical variables, frequency tables were constructed with their respective percentages, 95 % confidence intervals, and p-values to compare proportions. A p-value < 0.05 was considered statistically significant.

The Mann-Whitney U test was used to assess differences in median values between groups based on sex and urban or rural origin. The Kruskal-Wallis test was used to evaluate differences among groups by region, department, and educational level. The Chi-square test was applied to analyze differences in proportions. The Bonferroni correction was used as a post hoc test to identify specific differences in proportions or means between two groups.

To construct the logistic regression model, a correlation matrix with a threshold of ±0.7 was used to identify and eliminate highly correlated predictors to avoid multicollinearity. Subsequently, the model's balance was evaluated by analyzing the depression variable, comparing the proportions of positive and negative cases using distribution graphs, and applying the Chi-square test to identify significant differences in their distributions.

To correct the imbalance between classes, oversampling was applied using the "ROSE" package in RStudio, using the "ovun.sample" function using the "over" method to increase the number of samples in the minority class and balance the training dataset. A binomial logistic regression was performed using machine learning models, with 80 % of the data used for training and 20 % for testing. The model was optimized using machine learning techniques, including cross-validation, hyperparameter tuning with grid search, and multiple iterations as needed.

Categorical data imputation was performed using the mode. Finally, a Monte Carlo simulation was performed with 100 runs of the logistic regression model, adjusting the model with random subsets and calculating the average area under the curve (AUC) to evaluate its overall performance. The model resulting from the simulations was used for multivariate analysis.

The effect of confounding variables was identified and controlled by adjusting covariates in the model and analyzing subgroups of young adults aged 18 to 59 and adults aged 60 and older, according to the NMHS. The goodness-of-fit and accuracy of the model were assessed using *likelihood ratio* tests, ROC curves, and confusion matrices.

A clustering analysis was performed using variables measuring aspects of individuals' well-being and health to classify departments by risk level. A cluster analysis was performed using the k-means algorithm based on variables related to the population's well-being and health to classify the departments by risk level. The number of clusters was set to three using the elbow method. To evaluate the cluster analysis, the silhouette index was used, with values > 0.25 indicating acceptable separation between clusters.

The variables included the integration index, the participation index, and the organization index. Mental and emotional health measures were also incorporated, including COVID-19-related stress and functional disability, measured using the WHODAS score. Aspects of resilience and emotional management were also considered.

Suicide risk factors included variables related to suicidal ideation and behavior. In addition, variables related to substance use, such as tobacco, alcohol, and other substance use, as well as the degree of PTSD and anxiety, were taken into account.

RStudio version 4.3.2 was used for data processing and analysis, as well as for geospatial analysis. The map was represented by a color gradient at the departmental level.

The research was conducted in accordance with Good Clinical Practices. The database was coded to maintain participant confidentiality, and the study protocol was approved by the INS ethics committee under registration number CINS/2025/003.

Results

A total of 7249 adults were analyzed, of whom 55.4 % were from rural areas ($p < 0.01$). Women accounted for 69.9 % of participants ($p < 0.001$). The median age of the population was 45 years (IR 31-61), with a minimum age of 18 years and a maximum age of 97 years, $p < 0.01$

In the population studied, 22.8 % (1655) of participants had some degree of depression, $p < 0.001$. Participants with depression had a median age of 48 years (IR 33-63.5), while the median age of participants without depression was 44 years (IR 31-60), $p < 0.001$. The departments with the highest proportion of people with some degree of depression were Cuscatlán (29.7 %), Morazán (27.2 %), and Chalatenango (26.8 %), followed by San Vicente (25.3 %) and San Salvador (24.4 %).

In the pair comparisons evaluated with Bonferroni, significant differences were identified in some departments. Sonsonate showed differences compared to Chalatenango (p = 0.029). La Unión showed differences compared to Chalatenango (p = 0.0014) and La Libertad (p = 0.0041). No significant differences were detected in the remaining comparisons.

When stratified by sex, men with depression had a median age of 50 years (IR 32-68) compared to 46 years (IR 31-63) in those without depression. In women, the median age was 48 years (IR 33-62.2) in those with depression and 43 years (IR 31-59) in those without depression. These differences were statistically significant in both men (p = 0.014) and women ($p < 0.001$).

Differences were found between all groups with and without depression, $p < 0.01$ (Table 1). When analyzing the groups of people with depression, no significant differences were found, except for the variables of sex, age group, economic capacity, and UBN, $p < 0.01$.

Table 2 shows the relationship between depression and other mental health variables. Significant differences ($p < 0.01$) were identified with the experience of discrimination, COVID-19-related stress, anxiety, post-traumatic stress disorder (PTSD) and its degrees, as well as suicidal ideation and behavior.

Table 3 presents the overall results of the multivariate model. The factors with the strongest association with depression were anxiety (OR 10.385), PTSD (OR 4.471), COVID-19 stress (OR 2.42), suicidal ideation (OR 1.968), being female (OR 1.291), recent discrimination (OR 1.338), UBN (OR 1.192), and functional disability (OR 1.044), all with $p < 0.05$. The average AUC was 0.836.

In young adults (Table 4), depression was associated with anxiety (OR 9.301), PTSD (OR 5.462), suicidal ideation (OR 2.167), COVID-19 stress (OR 2.052), female sex (OR 1.593), discrimination in the last 12 months (OR 1.399), unmet basic needs (OR 1.264), and WHODAS score (OR 1.054). The model's performance was high (mean AUC 0.854; SD 0.014), $p < 0.05$.

In older adults (Table 4), associations were observed with anxiety (OR 11.579), PTSD (OR 6.910), suicidal ideation (OR 2.601), female sex (OR 1.465), and WHODAS score (OR 1.040). The model showed high discriminatory power (mean AUC = 0.838; SD = 0.017), $p < 0.05$.

Geospatial analysis and clustering analysis

Clustering analysis identified three distinct groups based on risk level: high, moderate, and low. The reported values correspond to the normalized averages for each variable within each group. In El Salvador, the majority of the population was classified as low risk (75.7 %), while 17.6 % were classified as high risk and 6.7 % as moderate risk.

At the departmental level, Usulután (81.5 %), La Libertad (79.5 %), and San Miguel (78.6 %) had the highest proportions of the population at low risk. In comparison, moderate risk was most common in La Paz (12.4 %) and Cuscatlán (11.1 %). Regarding high risk, the highest values were recorded in Morazán (26.4 %), Chalatenango (21.2 %), and Santa Ana (20.3 %) (Figure 1).

The highest-risk group was characterized by low levels of social integration, participation, and organization, indicating limited community cohesion and poor social support. This group had high levels of stress associated with the COVID-19 pandemic, high WHODAS scores, and low levels of resilience. In this profile, suicide risk, both in terms of ideation and attempts, was low, and tobacco and alcohol consumption remained at moderate levels.

The intermediate risk group showed low levels of integration and participation. However, they reported stress due to COVID-19 and high WHODAS scores. Resilience was low, but better emotional management was identified. This segment showed a higher frequency of suicidal ideation and attempts, as well as higher alcohol and tobacco consumption compared to the other groups.

Table 1. Classification of the population according to the presence of depression and sociodemographic variables, NMHS 2022

Variable	Category	Depression						Total	%
		Yes	%	95 % CI	No	%	95 % CI		
Area	Rural	921	22.9	(21.5 - 24.3)	3095	77.1	(75.7 - 78.5)	4016	55.4
	Urban	734	22.7	(21.3 - 24.1)	2499	77.3	(75.9 - 78.7)	3233	44.6
Region	Eastern	345	21.3	(19.9 - 22.7)	1276	78.7	(77.3 - 80.1)	1621	22.4
	Western	345	22.0	(20.6 - 23.4)	1221	78.0	(76.6 - 79.4)	1566	21.6
	Paracentral	354	24.9	(23.4 - 26.4)	1065	75.1	(73.6 - 76.6)	1419	19.6
	Central	299	21.9	(20.5 - 23.3)	1064	78.1	(76.7 - 79.5)	1363	18.8
	Metropolitan	312	24.4	(22.9 - 25.9)	968	75.6	(74.1 - 77.1)	1280	17.7
Sex	Men	327	15.0	(13.7 - 16.3)	1856	85.0	(83.7 - 86.3)	2183	30.1
	Female	1328	26.2	(24.8 - 27.6)	3738	73.8	(72.4 - 75.2)	5066	69.9
Age group	Under 20 years	50	25.0	(18.3 - 31.7)	150	75.0	(68.3 - 81.7)	200	2.8
	20 to 29 years	288	20.9	(19.3 - 22.5)	1088	79.1	(77.5 - 80.7)	1376	19.0
	30 to 39 years	245	18.9	(17.3 - 20.5)	1053	81.1	(79.5 - 82.7)	1298	17.9
	40 to 49 years	297	22.8	(21.2 - 24.4)	1008	77.2	(75.6 - 78.8)	1305	18.0
	50 to 59 years	271	24.7	(23.1 - 26.3)	828	75.3	(73.7 - 76.9)	1099	15.2
	Over 60 years	504	25.6	(24.1 - 27.1)	1467	74.4	(73.0 - 75.8)	1971	27.2
Housing quality	Yes	1430	22.6	(21.5 - 23.7)	4897	77.4	(76.3 - 78.5)	6327	87.3
	No	225	24.4	(21.0 - 27.8)	697	75.6	(72.2 - 79.0)	922	12.7
Overcrowding	Yes	101	24.1	(19.5 - 28.7)	318	75.9	(71.3 - 80.5)	419	5.8
	No	1530	22.7	(21.9 - 23.5)	5197	77.3	(76.5 - 78.1)	6727	92.8
	No data	24	23.3	(14.4 - 32.2)	79	76.7	(67.8 - 85.6)	103	1.4
Access to housing	Yes	1357	22.6	(21.5 - 23.7)	4637	77.4	(76.3 - 78.5)	5994	82.7
	No	275	23.8	(21.0 - 26.6)	881	76.2	(73.4 - 78.6)	1156	15.9
	No data	23	23.2	(12.5 - 33.9)	76	76.8	(66.1 - 87.5)	99	1.4
Access to healthcare	Yes	1602	22.9	(21.9 - 23.9)	5399	77.1	(76.1 - 78.1)	7001	96.6
	No	47	21.9	(14.3 - 29.5)	168	78.1	(70.5 - 85.7)	215	3.0
	No data	6	18.2	(6.3 - 30.1)	27	81.8	(69.9 - 92.7)	33	0.5
Access to education	Yes	1631	22.9	(21.9 - 23.9)	5504	77.1	(76.1 - 78.1)	7135	98.4
	No	24	21.1	(12.8 - 29.4)	90	78.9	(70.6 - 87.2)	114	1.6
Economic capacity	Yes	817	18.6	(17.1 - 20.1)	3571	81.4	(79.9 - 82.9)	4388	60.5
	No	824	29.4	(27.8 - 31.0)	1977	70.6	(69.0 - 72.2)	2801	38.6
	No data	14	23.3	(9.6 - 37.0)	46	76.7	(63.0 - 90.4)	60	0.8
UBN*	Yes	915	27.0	(25.5 - 28.5)	2470	73.0	(71.5 - 74.5)	3385	46.7
	No	718	19.2	(17.9 - 20.5)	3029	80.8	(79.5 - 82.1)	3747	51.7
	No data	22	18.8	(11.4 - 26.2)	95	81.2	(73.8 - 88.6)	117	1.6
Total		1655	22.8	(21.8 - 23.8)	5594	77.2	(76.2 - 78.2)	7249	100.0

***UBN:** Unmet Basic Needs.

Table 2. Classification of the population according to the presence of depression and mental health variables, NMHS 2022

Variable	Category	Depression						Total	%	*p-value*
			%	95% CI	No	%	95% CI			
Discrimination	Yes	469	41.9	(39.5 - 44.3)	650	58.1	(55.7 - 60.5)	1119	15.4	< 0.01
	No	1186	19.3	(18.2 - 20.4)	4944	80.7	(79.6 - 81.8)	6130	84.6	
Level of stress due to COVID-19	No	33	9.4	(5.4 - 13.4)	319	90.6	(86.6 - 94.6)	352	4.9	< 0.01
	Very low	471	14.9	(13.5 - 16.3)	2690	85.1	(83.7 - 86.5)	3161	43.6	
	Low	843	26.8	(25.3 - 28.3)	2300	73.2	(71.7 - 74.7)	3143	43.4	
	Moderate	288	51.2	(48.4 - 54.0)	275	48.8	(45.9 - 51.7)	563	7.8	
	High	20	66.7	(49.1 - 84.3)	10	33.3	(15.7 - 50.9)	30	0.4	
Resilience	Low	598	39.4	(37.5 - 41.3)	918	60.6	(58.7 - 62.5)	1516	20.9	< 0.01
	Moderate	969	19.0	(17.8 - 20.2)	4119	81.0	(79.8 - 82.2)	5088	70.2	
	High	88	13.6	(11.0 - 16.2)	557	86.4	(83.8 - 89.0)	645	8.9	
Risk of tobacco use	Low	1549	22.7	(21.7 - 23.7)	5272	77.3	(76.3 - 78.3)	6821	94.1	< 0.01
	Moderate	100	24.3	(19.1 - 29.5)	312	75.7	(70.5 - 80.9)	412	5.7	
	High	6	37.5	(12.5 - 62.5)	10	62.5	(37.5 - 87.5)	16	0.2	
Risk of alcohol consumption	low	1584	22.6	(21.6 - 23.6)	5438	77.4	(76.4 - 78.4)	7022	96.9	< 0.01
	Moderate	61	29.5	(20.3 - 38.7)	146	70.5	(61.3 - 79.7)	207	2.9	
	high	10	50.0	(20.0 - 80.0)	10	50.0	(20.0 - 80.0)	20	0.3	
Risk of substance use	Low	1586	22.6	(21.6 - 23.6)	5439	77.4	(76.4 - 78.4)	7025	96.9	< 0.01
	Moderate	69	30.9	(23.5 - 38.3)	154	69.1	(61.7 - 76.5)	223	3.1	
	High	-	0.0	(0.0 - 0.0)	1	100.0	(100.0 - 100.0)	1	0.0	
PTSD* severity	No	1311	19.3	(18.2 - 20.4)	5496	80.7	(79.6 - 81.8)	6807	93.9	< 0.01
	Mild-Moderate	273	74.4	(68.1 - 80.7)	94	25.6	(19.3 - 31.7)	367	5.1	
	Moderate-Severe	66	94.3	(84.5 - 100.0)	4	5.7	(0.0 - 15.5)	70	1.0	
	Extremely severe	5	100.0	(100.0 - 100.0)	0	0	(0.0 - 0.0)	5	0.1	
Level of anxiety	No	679	11.6	(10.5 - 12.7)	5158	88.4	(87.3 - 89.5)	5837	80.5	< 0.01
	Mild	742	64.1	(61.5 - 66.7)	416	35.9	(33.3 - 38.5)	1158	16.0	
	Moderate	172	90.1	(85.5 - 94.7)	19	9.9	(5.3 - 14.5)	191	2.6	
	Severe	62	98.4	(93.9 - 100.0)	1	1.6	(0.0 - 6.1)	63	0.9	
Suicidal behavior	Yes	73	69.5	(60.0 - 79.0)	32	30.5	(21.0 - 40.0)	105	1.4	< 0.01
	No	1582	22.1	(21.5 - 22.7)	5562	77.9	(77.3 - 78.5)	7144	98.6	
Suicidal ideation	Yes	337	68.2	(64.1 - 72.3)	157	31.8	(79.6 - 81.5)	494	6.8	< 0.01
	No	1318	19.5	(18.6 - 20.4)	5437	80.5	(27.7 - 35.9)	6755	93.2	
Total		1655	22.8	(21.8 - 23.8)	5594	77.2	(76.2 - 78.2)	7249	100.0	< 0.01

* **PTSD:** Post-traumatic stress disorder.

Table 3. Multivariate analysis of depression

Variable	Coefficient	OR	95 % CI	Standard error	*z*-score	*p*-value
Intercept	0.021	-	0.011–0.041	0.336	-11.51	<0.001
Anxiety	2.340	10.385	8.760–12.310	0.087	26.97	<0.001
PTSD*	1,498	4.471	3.257–6.138	0.162	9.26	<0.001
Presence of stress due to COVID-19	0.886	2.425	1.437–4.092	0.267	3.32	0.001
Suicidal ideation	0.677	1.968	1.605–2.414	0.104	6.50	<0.001
Low level of resilience	0.631	1.879	1.310–2.696	0.184	3.43	0.001
Moderate to high substance use	0.337	1.401	0.893–2.199	0.230	1.47	0.142
Discrimination <12 months	0.291	1.338	1.090–1.643	0.105	2.78	0.005
Female	0.255	1.291	1.072–1.553	0.095	2.70	0.007
UBN**	0.176	1.192	1.016–1.399	0.082	2.15	0.031
WHODAS score	0.043	1.044	1.038–1.051	0.003	13.56	<0.001
Suicidal behavior	-0.025	0.975	0.433–2.195	0.414	-0.06	0.951
Community participation index	-0.079	0.924	0.836–1.020	0.051	-1.56	0.119

Average AUC: 0.836 Standard Deviation of AUC: 0.010 Wald test: < 0.01 Likelihood test: < 0.01
*** PTSD:** Post-traumatic stress disorder.
****UBN:** Unmet Basic Needs.

Table 4. Multivariate analysis of depression in young adults and older adults

Subgroup	Variable	Coefficient	OR	95 % CI	Standard error	*Z-score*	*p-value*
Young adult	Intercept	0.030	-	0.014–0.065	0.392	-8.95	< 0.001
	Anxiety	2.230	9.301	7.633–11.334	0.101	22.11	< 0.001
	TEPT	1.698	5.462	3.766–7.922	0.190	8.95	< 0.001
	Suicidal ideation	0.773	2.167	1.732–2.712	0.114	6.76	< 0.001
	Presence of stress due to COVID-19	0.719	2.052	1.119–3.765	0.310	2.32	0.020
	Female	0.466	1.593	1.262–2.010	0.119	3.92	< 0.001
	Discrimination <12 months	0.336	1.399	1.099–1.780	0.123	2.73	< 0.001
	UBN	0.234	1.264	1.047–1.525	0.096	2.44	0.006
	WHODAS score	0.053	1.054	1.043–1.066	0.006	9.45	0.015
	Community participation index	0.032	1.033	0.908–1.174	0.066	0.50	< 0.001
	Age	0.000	1.000	0.992–1.009	0.004	0.00	0.625
	Community organization index	-0.029	0.971	0.855–1.104	0.065	-0.45	0.907
	Community integration index	-0.074	0.929	0.804–1.074	0.074	-1.00	0.659
Older adult	Intercept	0.056	-	0.009–0.325	0.915	-3.15	0.001
	Anxiety	2.449	11,579	8,233–16,285	0.174	14.08	< 0.001
	PTSD	1,933	6.910	3.146–15.177	0.401	4.82	< 0.001
	Suicidal ideation	0.956	2.601	1.467–4.613	0.292	3.27	0.001
	Female	0.382	1.465	1.057–2.030	0.166	2.29	0.022
	UBN	0.212	1.236	0.916–1.667	0.153	1.39	0.165
	Discrimination <12 months	0.043	1.044	0.676–1.612	0.222	0.19	0.845
	WHODAS score	0.039	1.04	1.030–1.050	0.005	7.99	< 0.001
	Neurocognitive impairment	0.015	1.015	0.701–1.468	0.189	0.08	0.939
	Community organization index	0.013	1.013	0.830–1.237	0.102	0.13	0.896
	Age	0.005	1.005	0.984–1.027	0.011	0.46	0.631
	Community integration index	-0.087	0.917	0.747–1.127	0.105	-0.83	0.412
	Presence of stress due to COVID-19	-0.200	0.819	0.405–1.658	0.360	-0.56	0.580
	Suicidal behavior	-1.363	0.256	0.002–27.689	2.433	-0.56	0.568

Young adult Average AUC 0.854, standard deviation 0.014 Wald test < 0.01 Likelihood test < 0.01.
Older adult Average AUC 0.838, standard deviation 0.017 Wald test < 0.01 Likelihood test < 0.01.
***PTSD:** Post-traumatic stress disorder.
***UBN:** Unmet basic needs.

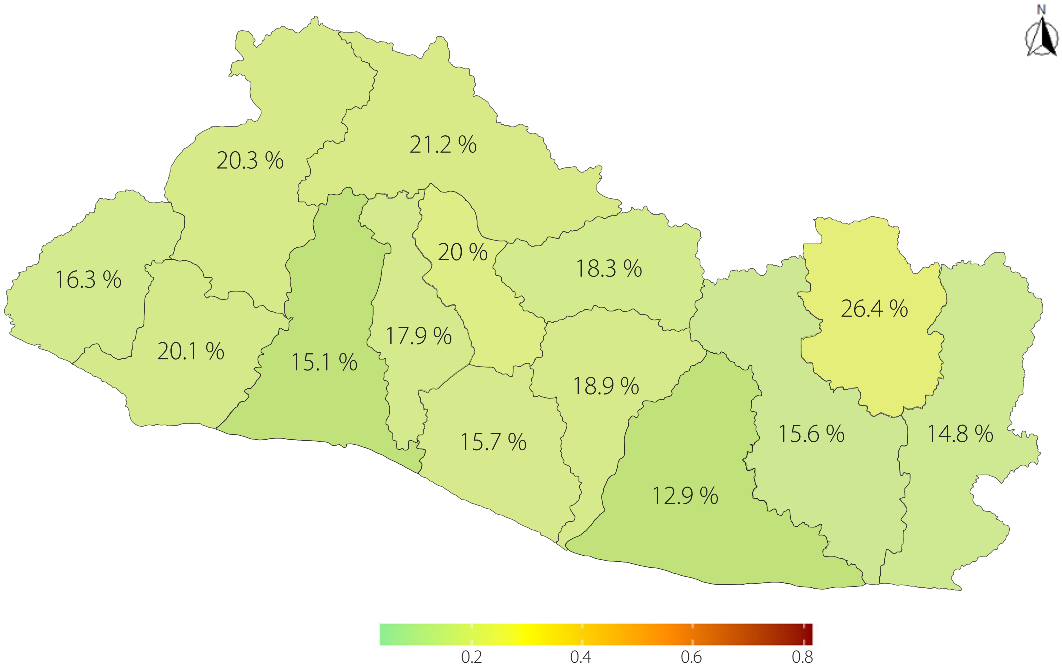

Figure 1. Proportion of high risk by department, NMHS 2021, El Salvador.

The lowest-risk group showed the highest levels of integration, participation, and organization. Stress and the WHODAS index were low, and resilience was highest among all groups. This group was characterized by better emotional management, lower suicide risk, and low levels of tobacco and alcohol consumption. The average silhouette index was 0.31, a value consistent with an acceptable separation between groups.

Discussion

This study offers insight into the prevalence and factors associated with depression in the adult and older adult population of El Salvador. The findings highlight the magnitude of this mental health problem, its multifactorial nature, and its exacerbation in the general population following the pandemic.

An important aspect of the analysis is the identification of various risk factors that contribute to depression in El Salvador. The results show a significant influence of sociodemographic variables, with greater vulnerability observed among women across age groups. Likewise, geographical variations in the prevalence and distribution of risk factors are identified, reflecting the influence of local contexts and structural conditions that may affect the onset and persistence of depression across different regions of the country.[15,16]

This finding highlights the particular dynamics between men and women[17], as well as the complex interactions among biological, sociodemographic, and sociocultural factors, underscoring the need to implement gender-sensitive strategies tailored to each territorial context.[18]

At the neuroendocrine level, both anxiety and depression are characterized by hyperactivation of the hypothalamic-pituitary-adrenal (HPA) axis, resulting in chronic elevations of cortisol and dysregulation of stress response systems.[19] This neuroendocrine alteration is associated with dysfunctions in neurotransmission systems and with the activation of neuroinflammatory processes that perpetuate symptoms, with greater expression in women, attributed to the interaction between reproductive hormones and the immune system.[20]

Anxiety also showed a significant association with depression. This relationship can be explained by the common biological and psychological mechanisms that favor the simultaneous onset of symptoms.[19] Recent research has identified bridging symptoms and particular characteristics in the interaction between anxiety and depression, suggesting the existence of differentiated neural circuits and heterogeneous activation of the HPA axis.[19] Likewise, a common comorbidity factor, known as the cb factor, has been described and can be predicted using edge-centered connectomes, with hereditary genetic markers that could explain the hereditary aggregation of depression.[21]

On the other hand, there are multiple factors that influence the prevalence of mental and physical health, both between countries and within the same territory.[22]

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Variations within a territory create unequal conditions that are reflected in how mental disorders are distributed geographically.[23] These differences increase when combined with socioeconomic inequalities, as they directly affect quality of life and opportunities for access to basic resources.[23] In this study, departments such as Morazán and Chalatenango showed the highest risk proportions, possibly related to the impact of armed conflict and specific socioeconomic and sociodemographic characteristics that, together, are associated with a higher prevalence of depression.

The analysis of machine learning models identified three profiles of individuals based on factors associated with depression. The first group was characterized by a high prevalence of risk factors, such as being female, having a low socioeconomic status, and experiencing high levels of stress, anxiety, and substance use, which was associated with higher levels of depressive symptoms.[24]

In contrast, the third group had a more favorable profile, with a lower presence of these factors and, consequently, a lower prevalence of depressive symptoms. The main difference between the two groups was the level of community participation and resilience, which were significantly higher in the low-risk group, acting as protective factors against depression. Other research has also reported a direct relationship between the presence of these factors and depression,[25] supporting the need to implement comprehensive mental health prevention and promotion strategies that address the identified determinants.[26]

Another factor that showed a significant association was the degree of functional disability, assessed using the WHODAS score. As difficulties in carrying out daily activities increased, so did the likelihood of experiencing depressive symptoms.[27] Limitations in personal performance, dependence on others, and loss of autonomy can lead to feelings of frustration, isolation, and uselessness, which are closely linked to emotional state.[28]

In this study, individuals who experienced high levels of stress related to the COVID-19 pandemic had significantly increased depressive symptoms. Fear of contagion, grief over the loss of loved ones, prolonged confinement, and economic uncertainty created an environment conducive to increased mental health problems.[29] Other research has confirmed the short- and long-term effects of this health crisis on mental health[30], reinforcing the need to consider people's social and emotional context when designing and implementing diagnostic, coping, and psychosocial support strategies aimed at mitigating the adverse effects of the pandemic.[26]

A relevant finding of this research was the strong association between PTSD and depression. People who have experienced traumatic events, particularly those that have not been adequately treated, are at greater risk of developing depressive symptoms.[31] Comorbidity between PTSD and depression is not only common, but is also associated with poorer therapeutic outcomes.[31]

Neuroimaging studies have identified both similarities and differences in brain activation patterns between PTSD and major depressive disorder, suggesting the existence of partially shared neural networks, as well as circuits specific to each disorder, with potential usefulness for guiding common and differentiated diagnostic and therapeutic strategies depending on the case.[32]

In this context, PTSD is particularly relevant, as it has been linked to elevated levels of suicide risk[33], especially when the results of this research confirmed an association between depression and suicidal ideation. Suicidal ideation is strongly related to the evolution of depression severity.[34]

A low level of resilience was identified as being associated with a higher risk of depression. Resilience operates as an internal resource that facilitates adaptation and response to adverse situations.[35] When resilience levels are low, people become more vulnerable to the emotional impact of problems, which increases the likelihood of developing depressive symptoms.[35] In addition, it has been observed that high levels of resilience can significantly reduce the risk of depression, especially among middle-aged and older adults, which could explain the differences between the factors found among the groups.[36]

Likewise, it was identified that UNB are linked to a higher risk of depression, especially in the young population. Poverty, lack of basic services, and precarious living conditions create environments of constant stress that affect mental health.[37] This finding reinforces the idea that depression not only has individual causes but is also influenced by the structural conditions in which people live,[37] in addition to generating tensions and ethical dilemmas in the therapeutic space for physicians working with patients affected by poverty and mental illness.[38]

On the other hand, although in various contexts community ties can act as a protective factor by creating safe and inclusive environments, no association was found in this population.[39,40] This difference could be due to the type or quality of participation being insufficient to generate a positive effect, especially given that the data were collected during the COVID-19 pandemic, when many forms of community participation were limited.[30]

Similarly, substance use did not show a significant association with depression. Although a relationship between substance use and affective disorders has been documented, the absence of an association could be due to variations in consumption patterns or the influence of confounding factors.[41] Current evidence indicates that substance use disorder is associated with greater severity of depressive symptoms, both cross-sectionally and over time.[41]

The study has some limitations, including the use of secondary data; nevertheless, the results constitute a solid basis for future research and for the formulation of public policies. This contribution is based on the identification of the multifactorial nature of depression, in which biological and psychological factors, as well as significant life experiences, converge. In addition, the application of robust statistical models, validated using machine learning models, yielded consistent and promising results on depression in El Salvador, based on a nationally representative sample.

Conclusion

Depression is determined by a complex interaction of psychological, social, structural, and individual factors, influenced and aggravated by environmental and geographical conditions that shape its distribution and deepen existing inequalities.

When compared with the global prevalence, a high frequency of depressive symptoms was found, particularly in women and in people with other mental health disorders or exposed to adverse living conditions. Geographical differences were also identified between risk groups: the highest risk group concentrated a greater number of vulnerability factors and fewer protective factors, while the lowest risk group had a greater presence of protective factors and less exposure to risk.

Depression is associated with other mental health problems such as anxiety, post- traumatic stress disorder, suicidal ideation, discrimination, unmet basic needs, and stress associated with the COVID-19 pandemic. Meanwhile, resilience and community support acted as protective factors.

Ethical aspects

The authors state that they have complied with the provisions of the Declaration of Helsinki and international ethical guidelines for health-related research involving human subjects.

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