Original article

Machine learning to identify factors associated with mild cognitive impairment in older adults in El Salvador

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Abstract
Introduction. Mild cognitive impairment in older adults represents an emerging public health challenge in Latin America due to its prevalence, progression to dementia, and functional, emotional, and social repercussions. In El Salvador, local evidence is needed to guide interventions. **Objective.** To analyze the factors associated with mild cognitive impairment in older adults in El Salvador. **Methodology.** An analytical cross-sectional study was conducted using data from the 2022 National Mental Health Survey. A total of 1897 older adults with complete records were analyzed. Descriptive analyses, multivariate logistic regression as a supervised prediction model, oversampling of the minority group with mild cognitive impairment using ROSE to reduce imbalance, cross-validation, Monte Carlo simulations, and K-means clustering to characterize territorial vulnerability profiles were applied in RStudio 4.5.0. **Results.** The prevalence of mild cognitive impairment in older adults was 17.7 %. The probability of the event increased with age (OR 1.05), female sex (OR 1.51), symptoms of anxiety and depression (OR 1.39 and OR 1.04, respectively), and age discrimination (OR 1.79). In contrast, literacy (OR 0.26), a higher socioeconomic status (OR 0.90), living in urban areas (OR 0.75), and labor inactivity (OR 0.55) showed a protective association ($p < 0.05$). The model demonstrated moderate discriminatory capacity (AUC 0.75). Clustering identified a higher concentration of highly vulnerable profiles in Morazán, Cabañas, and La Unión. **Conclusion.** Mild cognitive impairment in older Salvadoran adults is multifactorial. These findings can guide timely screening, comprehensive care, and territorial public policies.

Keywords
Cognitive Dysfunction, Machine Learning, Mental Health.

Resumen
Introducción. El deterioro cognitivo leve en adultos mayores representa un desafío emergente de salud pública en Latinoamérica por su prevalencia, progresión a demencia y repercusiones funcionales, emocionales y sociales. En El Salvador, se requiere evidencia local para orientar intervenciones. **Objetivo.** Analizar los factores asociados al deterioro cognitivo leve en adultos mayores de El Salvador. **Metodología.** Se realizó un estudio transversal analítico con datos de la Encuesta Nacional de Salud Mental 2022. Se analizaron 1897 adultos mayores. Se aplicaron análisis descriptivos, regresión logística multivariada como modelo de aprendizaje supervisado, y además se utilizó el desbalance de clases se manejó mediante el método de sobremuestreo. El modelo se optimizó con validación cruzada y simulaciones de Monte Carlo. El agrupamiento fue por K-means para caracterizar perfiles territoriales de vulnerabilidad, en RStudio 4.5.0. **Resultados.** La prevalencia de deterioro cognitivo leve fue del 17,7 %. La probabilidad del evento aumentó con la edad (OR 1,05), el sexo femenino (OR 1,51), los síntomas de ansiedad y depresión (OR 1,39; OR 1,04), y la discriminación por edad (OR 1,79). En contraste, la alfabetización (OR 0,26), un mayor nivel de estatus socioeconómico (OR 0,90), residir en zonas urbanas (OR 0,75) y la inactividad laboral (OR 0,55) mostraron asociación protectora ($p < 0,05$). El modelo presentó capacidad discriminativa moderada (AUC 0,75). El agrupamiento identificó mayor concentración de perfiles de alta vulnerabilidad en Morazán, Cabañas y La Unión. **Conclusión.** El deterioro cognitivo leve en adultos mayores salvadoreños es multifactorial. Estos hallazgos pueden orientar un tamizaje oportuno, atención integral y políticas públicas territoriales.

Palabras clave
Disfunción Cognitiva, Aprendizaje Automático, Salud Mental.

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Aprendizaje automático para identificar factores asociados al deterioro cognitivo leve en adultos mayores de El Salvador

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Introduction

Population aging is one of the major demographic phenomena of the 21st century[1] and is driven by the sustained decline in birth rates and the increase in life expectancy.[2] In 2019, an estimated 703 million people worldwide were aged 65 or older, and this figure is projected to exceed 1.5 billion by 2050.[1] In Latin America and the Caribbean, this demographic transition is advancing rapidly. In El Salvador, it is projected that by 2042, 26.7 % of the population will be older adults.[3,4] This represents a significant challenge for health systems, social protection, and public policy formulation.[5]

Cognitive impairment is a condition characterized by the progressive decline of mental functions, such as memory, language, attention, and reasoning.[6-8] Mild cognitive impairment (MCI) represents an intermediate state between normal cognitive aging and major neurocognitive disorders, and is not an inevitable part of the aging process.[9] Although it does not severely compromise functional autonomy, it significantly increases the risk of progression to dementia, such as Alzheimer's disease, with annual conversion rates ranging from 8 % to 15 %.[9-11]

Globally, the estimated prevalence of MCI is 19 %, ranging from 5.1 % to 41 %, influenced by demographic, cultural, and socioeconomic factors.[1,12] Latin America and the Caribbean report MCI prevalences ranging from 6.8 % to 25.5 %, indicating significant regional heterogeneity.[13] Evidence suggests that advanced age, gender, low educational attainment, socioeconomic vulnerability, multimorbidity, and psychosocial determinants influence its onset and progression.[8,13] In comparable countries in the region, such as Chile and Colombia, associations have been documented with older age, female sex, lower socioeconomic status, and low educational attainment.[12,14,15]

In El Salvador, there is limited scientific evidence regarding the magnitude and factors associated with MCI. The 2022 National Mental Health Survey (NMHS 2022), conducted by the National Institute of Health (NIH), is a high-quality source of information for analyzing this issue from a population-based perspective.[16] In Central America, available evidence is also limited; however, recent studies in Panama have identified predictors of cognitive decline in older women, reinforcing the regional relevance of the problem.[17]

In this context, predictive modeling and data analysis techniques have proven useful for studying MCI by facilitating the identification of complex risk patterns and improving population stratification.[18-22] Conceptual reviews and recent studies have demonstrated the utility of supervised models for identifying factors associated with cognitive decline and optimizing early detection through the integrated analysis of clinical, functional, behavioral, and sleep variables, biomarkers, and neuroimaging.[18,19,21,23] These models have been applied to support early detection and guide public health decisions.[18-22] However, these approaches do not replace clinical evaluation or traditional epidemiological analysis; rather, they complement them by strengthening the identification of groups with greater vulnerability.[18,22]

From this perspective, a secondary analysis of the 2022 NMHS data was conducted to identify the sociodemographic, clinical, functional, and psychosocial factors associated with MCI in older adults in El Salvador, using an integrated approach involving epidemiological analysis, predictive modeling with supervised learning, and exploratory characterization of vulnerability profiles. This evidence aims to provide input for the design of strategies for timely screening, prevention, and healthy aging in the country.[24]

Methodology

We conducted an analytical cross-sectional study through secondary analysis of data from the 2022 NMHS, implemented by the Ministry of Health of El Salvador through NIH. The survey was designed to obtain nationally representative information on mental health problems in the population aged three years and older. To this end, specific questionnaires were administered to children (ages three to 12), adolescents (ages 13 to 17), adults (ages ≥ 18), and older adults (ages ≥ 60). The instruments were selected and adapted from previously validated and authorized scales. The NIH technical team conducted a structured search and technical review of the instruments; subsequently, these were evaluated and validated by psychologists and psychiatrists from the National Health System and professional mental health associations. Data collection took place between August and November 2022, involving 11 269 participants.[16]

For this study, the population consisted of individuals aged 60 years or older who completed the modules on adults, housing, and household members. Cases with a complete record for the "Mild Cognitive Impairment" variable were included. The initial dataset contained 1958 records, of which 61 were excluded due to incomplete data in the outcome variable; therefore, the analysis was conducted with 1897 participants.

In the analysis, the primary variable was MCI, assessed using the SPMSQ (Short Portable Mental Status Questionnaire), which evaluates orientation, calculation, and memory. Participants with zero to two errors were considered to have no cognitive impairment, and those with three to four errors were classified as having MCI.[24]

The main independent variables included sociodemographic, clinical, functional, behavioral, and psychosocial factors. Sociodemographic variables included age, sex, area of residence, literacy, educational level, and socioeconomic status. The latter was constructed as a proxy variable for socioeconomic status using principal component analysis, integrating twelve indicators of material household conditions, access to basic services, overcrowding, and perceived income adequacy.[25,26] The resulting principal component was transformed into a three-level ordinal variable: low, medium, and high.

Functional variables were assessed using the WHODAS 2.0 (World Health Organization Disability Assessment Schedule 2.0), a World Health Organization instrument that measures limitations in functioning and social participation. Psychosocial variables included perceived community support, age discrimination, and resilience. Clinical variables include symptoms of depression, anxiety, pandemic-related stress, and suicidal ideation. Behavioral variables included alcohol, tobacco, and sedative use. The instruments used were the PHQ-9, GAD-7, PCL-5, C-SSRS, and ASSIST, all of which had been previously validated for the Salvadoran population. We extracted data directly from the survey, without any additional application or construction by the researchers.

For continuous variables, we assessed normality using the Anderson-Darling test. Due to the non-normal distribution, we used median and interquartile range (IQR) as measures of central tendency and dispersion, respectively. In addition, frequency tables were constructed with percentages and 95 % confidence intervals. Differences between medians were assessed using the Mann-Whitney U test, and differences in proportions using the chi-square test. A p-value < 0.05 was considered statistically significant.

We developed a multivariate logistic regression model as a supervised learning modeling approach to identify factors associated with MCI. Previously, multicollinearity among predictors was assessed using a correlation matrix, with a threshold of ± 0.7 to identify highly correlated variables. We verified model assumptions,, including the independence of observations and the linearity of the logit for continuous variables.

Missing values in the categorical variables used in the modeling were rare and were imputed using the mode. To address the class imbalance between participants with and without MCI, We applied oversampling of the minority class only to the training set, using the "ROSE" (Random OverSampling Examples) package in RStudio via the "ovun. sample" function with the "over" method.

The data were then split into 80 % for training and 20 % for testing. The model was trained using ten-fold cross-validation. We evaluated model performance using the ROC curve, the area under the curve (AUC), the confusion matrix, and the likelihood ratio test. Additionally, we performed internal validation using 100 Monte Carlo simulations with repeated random partitions of the training and test sets to estimate the average AUC as a robust measure of model stability.

We complenented the analysis with unsupervised machine learning techniques using K-means clustering to identify vulnerability profiles for MCI. Relevant variables were selected, including age, sex, socioeconomic status, depressive and anxiety symptoms, functionality, stress, resilience, di, discrimination, and cognitive stimulation, all of which were previously standardized. The optimal number of clusters was defined using the elbow method, and the population was classified into three vulnerability profiles-high, moderate, and low-based on the cumulative burden of adverse factors.

El Salvador is administratively organized into 14 departments, equivalent to provinces or states in other countries. Based on this structure, We conducted a descriptive cartographic analysis of the territorial distribution of vulnerability profiles by department. The proportion of participants classified as high vulnerability in each department was calculated and represented using thematic maps with color gradients. This component was exploratory and descriptive in nature, without applying spatial autocorrelation methods or geographic inferences.

Data processing and analysis were performed in RStudio version 4.5.0. This study was conducted in accordance with Good Clinical Practice. The data were anonymized to protect the confidentiality of the participants. The protocol was approved by the Ethics Committee of the National Institute of Health of El Salvador under registration number CEINS/2025/005.

Results

Demographic characteristics

A total of 1897 older adults who participated in the 2022 NMHS were analyzed. The median age was 69 years, (IQR) 64-75), with a minimum of 60 years and a maximum of 97 years. By area of residence, the median age in the urban area was 69 years (IQR 64-75), while in the rural area it was 68 years (IQR 63-74), $p < 0.05$. Fifty two point one percent of participants were from urban areas, $p < 0.05$. At the departmental level, San Salvador (83.1 %) and La Libertad (54.6 %) had the highest proportion of urban population. In contrast, Morazán (78.5 %), La Unión (77.4 %), Cuscatlán (67.7 %), Ahuachapán (66.3 %), and Sonsonate (57.1 %) showed a predominance of rural population, $p < 0.05$.

Regarding gender, 64.1 % of older adults were women ($p < 0.05$). At the departmental level, the predominance of women persisted, with La Paz (71.5 %), Cuscatlán (68.7 %), San Miguel (68.3 %), and San Salvador (68.0 %) standing out in most departments, $p < 0.05$; except in Ahuachapán (57.3 %) and Morazán (58.5 %). The median age was similar between men and women (69 years; 95 % IQR 64-75), $p < 0.05$.

Characterization of cases of mild cognitive impairment in older adults in El Salvador

Of the total older adults analyzed, 17.7 % had MCI, $p < 0.01$. The median age of cases was 73 years (IQR = 67-78), higher than that of those without this condition, $p < 0.01$, with a progressive increase in MCI observed as age advanced. The prevalence of MCI was higher in women (20.6 %) than in men (12.3 %), with the highest concentration in the 70-79 age group (45.1 %). By area of residence, 23.4 % of older adults in rural areas had MCI, compared with 12.3 % in urban areas ($p < 0.01$).

Likewise, MCI was more common among illiterate individuals (36.9 %) compared to literate individuals (10.6 %). Regarding socioeconomic status, 25.1 % of older adults in the low socioeconomic stratum had MCI, while in the middle and high strata the proportions were lower, at 14.8 % and 12.8 %, respectively. Regarding employment status, 25.0 % of unemployed older adults had MCI. However, of the total cases with MCI, 87.5 % were among those in the workforce, $p < 0.01$. (Table 1).

Based on health and functional status, 22.1 % of older adults who sought care in the public health system had MCI ($p < 0.01$). Prevalence was higher among those with functional limitations (22.3 %; $p < 0.01$), and within the group with MCI, 52.8 % reported some degree of limitation ($p > 0.05$). Regarding mental health, MCI was present in 19.6 % ($p < 0.01$) of those with depression and in 26.6 % ($p < 0.01$) of those reporting anxiety. Among the cases identified with MCI, 76.4 % had depression, and 27.2 % had anxiety, both with $p < 0.01$. Regarding habits related to well-being, 27.6 % of older adults with low cognitive stimulation and poor sleep quality had MCI, compared to lower proportions among those who reported high levels of stimulation (13.3 %) and adequate sleep (16.7 %) ($p < 0.01$). In the psychosocial domain, 21.6 % of those who experienced discrimination reported MCI ($p < 0.01$), a proportion that increased too 32.3 % among those who suffered age discrimination ($p < 0.01$). In addition, 23.6 % of older adults with low resilience exhibited MCI ($p < 0.01$) (Table 2).

In the analysis based on substance use, 8.9 % of older adults with a pattern of alcohol use classified as risky had MCI, while only 3.9 % of cases with MCI reported such use, $p <$ 0.05. Regarding the use of sedatives, 37.5 % of at-risk users had MCI, $p > 0.05$, although only 2.7 % of cases with MCI reported such use, $p < 0.05$. Regarding tobacco, the proportion of MCI was the same among those with risky consumption and those without (17.7 % in both groups; $p < 0.05$) (Table 2).

Multivariate analysis and validation of predictive performance

According to the multivariate logistic regression model, the factors that increased the probability of MCI were age-based discrimination in the past 12 months (OR 1.79; 95 % IQR 1.08-2.94), female gender (OR 1.51; 95 % IQR 1.16-1.97), anxiety (OR 1.39; 95 % IQR 1.01-1.91),depression (OR 1.04; 95 % IQR 1.01-1.07), and increasing age (OR 1.05; 95 % IQR 1.04-1.07), all with $p < 0.05$. In contrast, the following were associated with a lower probability of MCI: literacy (OR 0.26; 95 % IQR 0.20-0.34); being economically inactive or retired (OR 0.55; 95 % IQR 0.31-0.95); urban residence (OR 0.75; 95 % IQR 0.59-0.96);and a higher socioeconomic status index (OR 0.90; 95 % IQR 0.82-0.99), all with $p < 0.05$ (Table 3).

In evaluating predictive performance, the model demonstrated moderate discriminatory ability for identifying MCI in older adults. Internal validation using 100 Monte Carlo simulations with ten-fold cross-validation yielded an average AUC of 0.7567 with a standard deviation of 0.0221, indicating the model's internal stability. The final model was evaluated on the independent test set. The ROC curve showed an AUC of 0.7261 (95 % IQR 0.6592-0.7930), indicating an acceptable ability to distinguish between older adults with and without MCI (Figure 1).

In the best validation scenario, the overall accuracy of the model was 71.9 %, with a sensitivity of 66.5 %, specificity of 77.0 %, positive predictive value of 72.9 %, negative predictive value of 71.2 %, and balanced accuracy of 71.8 %. The likelihood ratio test showed a significant overall fit ($p < 0.01$).

Table 1. Sociodemographic characteristics of the population according to the presence of MCI, NMHS 2022

Characteristic	Mild cognitive impairment						Total		p value
	Yes			No					
	F	%	IC 95 %	F	%	IC 95 %	F	%	
Sex									
Female	251	20.6	(18.5-23.0)	965	79.4	(77.0-81.5)	1216	64.1	<0.01
Male	84	12.3	(10.1-15.0)	597	87.7	(85.0-89.9)	681	35.9	<0.01
Age group									
60 to 69 years	121	11.9	(10.0-140)	899	88.1	(86.0-90.0)	1020	53.8	<0.01
70 to 79 years	151	22.9	(19.9-26.3)	507	77.1	(73.7-80.1)	658	34.7	<0.01
≥ 80 years	63	28.8	(23.2-35.1)	156	71.2	(64.9-76.8)	219	11.5	<0.01
Area									
Rural	213	23.4	(20.8-26.3)	696	76.6	(73.7-79.2)	909	47.9	<0.01
Urban	122	12.3	(10.4-14.5)	866	87.7	(85.5-89.6)	988	52.1	<0.01
Region									
Eastern	85	21.1	(17.4-25.3)	318	78.9	(74.7-82.6)	403	21.2	<0.01
Paracentral	76	20.8	(16.9-25.2)	290	79.2	(74.8-83.1)	366	19.3	<0.01
Western	75	20.9	(17.0-25.4)	284	79.1	(74.6-83.0)	359	18.9	<0.01
Central	54	14.0	(10.9-17.9)	331	86.0	(82.1-98.1)	385	20.3	<0.01
Metropolitan	45	11.7	(8.9-15.3)	339	88.3	(84.7-91.7)	384	20.2	<0.01
Socioeconomic status									
Low	162	25.1	(21.9-28.6)	483	74.9	(71.4-78.1)	645	34.0	<0.01
Median	94	14.8	(12.3-17.8)	540	85.2	(82.2-87.7)	634	33.4	<0.01
High	79	12.8	(10.4-15.6)	539	87.2	(84.4-89.6)	618	32.6	<0.01
Literate									
Yes	146	10.6	(9.1-12.3)	1239	89.7	(87.7-90.9)	1382	72.9	<0.01
No	189	36.9	(32.8-41.2)	323	63.1	(58.8-67.2)	512	27.0	<0.01
Educational level									
Low	27	8.8	(6.1-12.5)	281	91.2	(87.5-93.9)	308	16.2	<0.01
Median	305	21.6	(19.5-23.8)	1109	78.4	(76.2-80.5)	1414	74.5	<0.01
High	3	1.7	(0.6-4.9)	172	98.3	(95.1-99.4)	175	9.2	<0.01
Employment status									
Employed	293	18.2	(17.4-25.3)	1318	81.8	(17.4-25.3)	1611	84.9	<0.01
Unemployed	32	25.0	(16.9-25.2)	116	90.6	(16.9-25.2)	128	6.7	<0.01
Retirement	8	5.4	(17.0-25.4)	120	81.1	(17.0-25.4)	148	7.8	<0.01
No data	2	20.0	(10.9-17.9)	8	80.0	(10.9-17.9)	10	05	<0.01
Total	335	17.7	(16.0-19.4)	1562	82.3	(80.6-84.0)	1897	100	<0.01

Table 2. Health conditions. functionality. and psychosocial factors of the population according to the presence of MCI. NMHS 2022

Characteristics	Mild cognitive impairment						Total		*p* value
	Yes			No					
	F	%	IC 95 %	F	%	IC 95 %	F	%	
Place of consultation									
Audience	229	22.1	(19.7 - 24.7)	808	77.9	(75.3 - 80.3)	1037	54.7	<0.01
Private	84	16.6	(13.6 - 20.1)	422	83.4	(79.9 - 86.4)	506	26.7	<0.01
Social Security	18	5.4	(3.4 - 8.4)	315	94.6	(91.6 - 96.6)	333	17.6	<0.01
Others	4	19.0	(7.7 - 40.0)	17	81.0	(60.0 - 92.3)	21	1.1	<0.01
Mental health diagnosis									
Yes	12	18.8	(11.1 - 30.0)	52	81.3	(70.0-88.9)	64	3.4	<0.01
No	320	17.5	(23.2 - 35.1)	1506	82.5	(80.7-84.2)	1826	96.3	<0.01
No data	3	42.9	(23.2 - 35.1)	4	57.1	(25.0-84.2)	7	0.4	1.01
Functional limitations									
Yes	177	22.3	(19.5 - 25.3)	617	77.7	(74.7 - 80.5)	794	41.9	<0.01
No	158	14.3	(12.4 - 16.5)	945	85.7	(83.5 - 87.6)	1103	58.1	<0.01
Sleep quality									
Bad	48	27.6	(21.5 - 34.7)	126	72.4	(65.3 - 78.5)	174	9.2	<0.01
Good	287	16.7	(15.0 -18.5)	1436	83.3	(81.5 - 85.0)	1723	90.8	<0.01
Cognitive Stimulation									
Low	24	27.6	(19.3 - 37.8)	63	72.4	(62.2 - 80.7)	87	4.6	<0.01
Moderate	142	26.2	(22.7 - 30.1)	399	73.8	(69.9 - 77.3)	541	28.5	<0.01
High	169	13.3	(11.6 - 15.3)	1100	86.7	(84.7 - 88.4)	1269	66.9	<0.01
Depression									
Yes	256	19.6	(17.6 - 21.9)	1047	80.4	(78.1 - 82.4)	1303	68.7	<0.01
No	79	13.3	(10.8 - 16.3)	515	86.7	(83.7 - 89.2)	594	31.3	<0.01
Anxiety									
Yes	91	26.6	(22.2 - 31.5)	251	73.4	(68.5 - 77.8)	342	18.0	<0.01
No	244	15.7	(14.0 - 17.6)	1311	84.3	(82.4 - 86.0)	1555	82.0	<0.01
COVID-19 stress									
Yes	323	17.9	(16.2 - 19.7)	1486	82.1	(80.3 - 83.8)	1809	95.4	<0.01
No	12	13.6	(8.0 - 22.3)	76	86.4	(77.7 - 92.0)	88	4.6	<0.01
Post-traumatic stress									
Yes	20	20.6	(13.8 - 29.7)	77	79.4	(70.3 - 86.2)	97	5.1	<0.01
No	315	17.5	(15.8 - 19.3)	1485	82.5	(80.7 - 84.2)	1800	94.9	<0.01
Overall discrimination									
Yes	57	21.6	(17.1 - 26.9)	207	78.4	(73.1 - 82.9)	264	13.9	<0.01
No	278	17.0	(15.3 - 18.9)	1355	83.0	(81.1 - 84.7)	1633	86.1	<0.01
Age discrimination									
Yes	31	32.3	(23.8 - 42.2)	65	67.7	(57.8 - 76.2)	96	5.1	<0.01
No	304	16.9	(15.2 - 18.7)	1497	83.1	(81.3 - 84.8)	1801	94.9	<0.01
Suicide risk									
Yes	29	26.1	(18.9 - 35.0)	82	73.9	(65.0 - 81.1)	111	5.9	<0.01
No	306	17.1	(15.5 - 19.0)	1480	82.9	(81.0 - 84.5)	1786	94.1	<0.01
Resilience									
Low	98	23.6	(19.8 - 27.9)	317	76.4	(72.1 - 80.2)	415	21.9	<0.01
Moderate	212	15.8	(13.9 - 17.8)	1130	84.2	(82.2 - 86.1)	1342	70.7	<0.01
High	25	17.9	(12.4 - 25.0)	115	82.1	(75.0 - 87.6)	140	7.4	<0.01
Perceived community									
Low	21	21.2	(14.3 - 30.3)	78	78.8	(69.7 - 85.7)	99	5.2	<0.01
Moderate	222	18.9	(16.8 - 21.3)	951	81.1	(78.7 - 83.2)	1173	61.8	<0.01
High	92	14.7	(12.2 - 17.7)	533	85.3	(82.3 - 87.8)	625	32.9	<0.01
Total	335	17.7	(16.0 - 19.4)	1562	82.3	(80.6 - 84.0)	1897	100	<0.01

Table 3. Multivariate analysis of mild cognitive impairment in older adults. NMHS 2022

Variable	Coefficients	OR	Standard error	Z value	IC95 %	*p* value
Intercept	-3.23	-	0.52	-6.19	(0.01-0.10)	< 0.01
Discrimination by age < 12 months	0.58	1.79	0.25	2.27	(1.08-2.94)	< 0.05
Female	0.41	1.51	0.13	3.08	(1.16-1.97)	< 0.05
Anxiety	0.33	1.39	0.16	2.00	(1.01-1.91)	< 0.05
Age	0.05	1.05	0.01	7.03	(1.04-1.07)	< 0.01
Depression	0.03	1.04	0.02	2.21	(1.01-1.07)	< 0.05
Socioeconomic status index	-0.10	0.90	0.05	-2.12	(0.82-0.99)	< 0.05
Urban area	-0.28	0.75	0.13	-2.25	(0.59-0.96)	< 0.05
Inactive status or retirement	-0.61	0.55	0.28	-2.13	(0.31-0.95)	< 0.05
Literate	-1.34	0.26	0.13	-10.42	(0.20-0.34)	< 0.01

Analysis of the clustering and spatial distribution of vulnerability profiles

The high-vulnerability cluster was characterized by greater functional disability (WHODAS), severe symptoms of depression and anxiety, COVID-19-related stress, experiences of age discrimination, low resilience, limited cognitive stimulation, older age, and lower socioeconomic status. The moderate vulnerability cluster grouped moderate symptoms of depression and anxiety, intermediate levels of functional disability, and intermediate resilience. The low vulnerability cluster showed better functioning, lower levels of emotional distress, high resilience, and adequate cognitive stimulation, constituting a relatively more favorable profile.

This analysis revealed a heterogeneous distribution of vulnerability to MCI among older adults in El Salvador. Of the total participants, 21.1 % (400) were classified as high vulnerability, 45.9 % (871) as moderate vulnerability, and 33.0 % (626) as low vulnerability. In terms of geographical distribution, the departments of Cabañas (30.7 %; 23), Morazán (27.7 %; 18), and La Unión (26.9 %; 25) had the highest proportion of older adults in the high-vulnerability category. In contrast, Ahuachapán (42.7 %; 38) and Santa Ana (38.0 %; 60) recorded the highest proportion of older adults in the low-vulnerability profile, $p < 0.05$ (Figure 2).

Discussion

Mild cognitive impairment in older adults is a multifactorial phenomenon determined by biological, emotional, social, and structural factors.[8,13] In this study, based on data from the 2022 NMHS, the prevalence of MCI was 17.7 %, a figure consistent with the range reported in Latin America and the Caribbean (6.8 % to 25.5 %) and comparable to Colombia (19.7 %), which supports the external validity of the findings in similar regional contexts.[13,14] In contrast, differences compared to Chile, where lower prevalences have been reported (9.1 % and 10.4 %), likely reflect variations in screening instruments, cutoff points, sociodemographic profiles, and contextual inequalities among populations.[2,7,15]

A key strength was the integration of classical epidemiological analysis with supervised learning predictive modeling, based on logistic regression with internal validation. To the best of our knowledge, this study represents one of the first approaches in El Salvador to combine epidemiological analysis, predictive modeling, and exploratory clustering of MCI in older adults. The model demonstrated moderate discriminatory power and utility for population stratification and screening prioritization, although it does not replace individual clinical evaluation.[18-22] In practical terms, this approach can support the early detection of groups with greater vulnerability, community-based follow-up, and the design of strategies for the prevention and surveillance of cognitive decline in primary care, especially in resource-limited settings.[22]

Depressive and anxiety symptoms showed a significant association with MCI, consistent with evidence documenting a close relationship between mental health and cognitive function in aging.[27,28] The observed magnitude was lower than that reported in Chile, where the presence of anxiety and depressive symptoms was associated with more than double the probability of cognitive decline (OR 2.27; 95 % CI 1.35-3.83).[2] Likewise, several studies

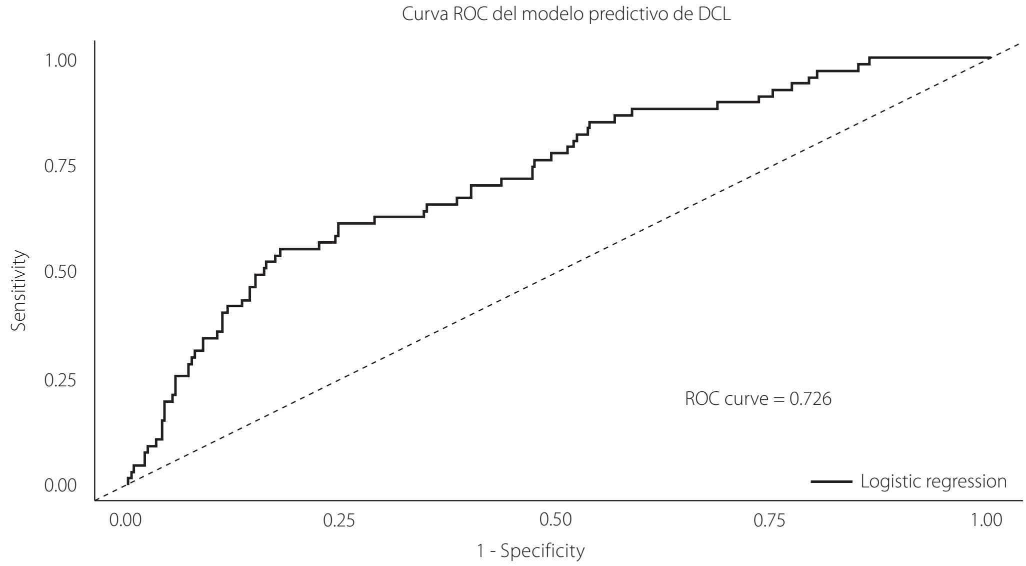

Figure 1. ROC curve of the final predictive model for mild cognitive impairment in older adults in El Salvador, NMHS 2022.

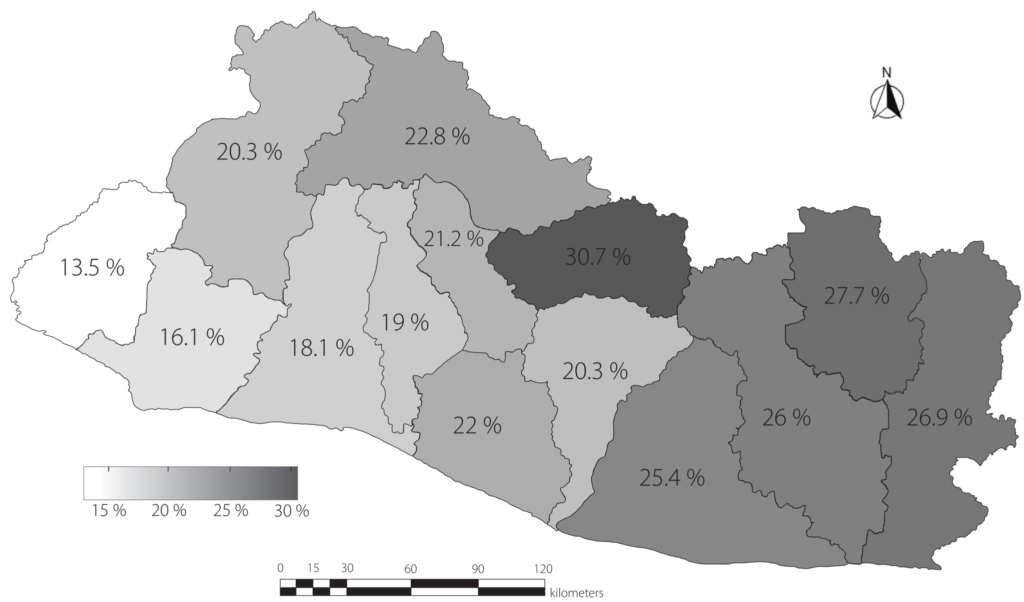

Figure 2. Geographic distribution of high-vulnerability profiles regarding mild cognitive impairment in older adults, NHMS 2022, El Salvador.

support a bidirectional relationship, in which affective symptoms and MCI mutually reinforce each other and accelerate functional decline.[27-32] Since mental health is a potentially modifiable factor, these results support the incorporation of joint screening for affective symptoms and cognitive function in primary care.[30-32]

The higher probability of MCI observed in women is consistent with Latin American studies reporting higher prevalence and cognitive decline in this group.[13,14] Evidence suggests that, although men have greater structural cognitive reserve, women exhibit symptoms from early neuropathological stages.[33] This pattern likely reflects the interaction between neurobiological changes linked to brain aging, a higher burden of comorbidities, and structural inequalities accumulated over the course of a lifetime.[17,33-35] These findings support the need to incorporate a gender-sensitive approach into prevention and screening strategies.[35]

The association between aging and MCI was consistent with the regional literature. In Chile, each additional year of life increased the probability of cognitive decline (OR 1.08; 95 % IQR 1.04-1.11; p = 0.001).[2] Similarly, studies in Peru and Mexico have documented a progressive increase in the prevalence of cognitive decline with age, especially after age 70.[12,36] This pattern supports the view that aging acts as a cumulative process of biological, functional, and social vulnerability, which can be intensified in contexts of inequality and reduced access to support and care networks.[37–39]

Another relevant finding was the association between age discrimination and MCI. This result suggests that ageism and other social determinants influence cognitive health beyond traditional biomedical factors.[40,41] Evidence shows that chronic discrimination increases stress, social isolation, and neuropsychological vulnerability, thereby promoting less healthy aging trajectories.[40-43] In this regard, this finding broadens the understanding of MCI as a phenomenon that is not only clinical but also socially conditioned, with relevant implications for healthy aging policies.

Among protective factors, literacy showed the greatest effect, consistent with cognitive reserve theory, which posits that education promotes more efficient neural networks and greater compensatory capacity against MCI.[44] This finding is consistent with studies from Colombia, where secondary or higher education reduced the probability of MCI by 71 % (adjusted OR 0.29; 95 % IQR 0.25-0.34), as well as in Peru and India, where low educational attainment has been associated with greater cognitive and functional decline.[8,12] Taken together, these results reinforce the role of education throughout the life course as a key determinant of healthy aging.

Similarly, inactivity or retirement was associated with a lower probability of mild cognitive impairment; however, this finding should be interpreted with caution, as it may reflect lower exposure to adverse work environments or chronic stress.[46,47] In Colombia, a higher probability of cognitive decline was reported among working-age individuals (OR 2.74), particularly in informal employment without social protection.[14] In India, although the results are inconclusive, it is suggested that retirement may promote mental health through a "relief effect" by reducing stressful cognitive demands.[46] However, reverse causality is also possible: cognitively healthy older adults may remain active for longer.[46,47]

Likewise, a higher socioeconomic status and living in urban areas were associated with a lower probability of MCI. These findings suggest that better material conditions, greater ability to meet basic needs, and better access to services may have a protective effect on cognitive health.[8,14,46] Similarly, living in urban areas may promote cognitive function due to greater availability of social and health services, as well as greater opportunities for social and cognitive engagement and stimulation, consistent with studies from Latin America.[13]

Furthermore, the cluster analysis identified profiles of vulnerability to MCI: high, moderate, and low, based on functional, emotional, and psychosocial burden, as well as their geographical distribution. Although this component was exploratory and does not allow for departmental inferences, it provided a useful approach for identifying patterns of vulnerability and guiding hypotheses, local surveillance, and program prioritization.

Studies in China and Italy have applied similar approaches to identify populations with higher cognitive vulnerability.[48,49] In Central America, where evidence remains scarce, this approach offers an innovative perspective for strengthening preventive planning.

However, the study has limitations. The cross-sectional design prevents the establishment of temporality or causality; the use of secondary data may introduce information bias and residual confounding; and the assessment of MCI was based on a brief scale, without complementary neuropsychological testing. Furthermore, the predictive model may have been subject to overfitting due to class balancing, although cross-validation and Monte Carlo simulations support its internal stability. Therefore, the findings should be interpreted with caution in terms of causality and individual prediction. Future studies should assess progression to dementia, incorporate biomarkers, and compare more complex algorithms to optimize individual and population-level prediction.

Conclusions

The results show that MCI in older Salvadoran adults is a multifactorial phenomenon, influenced by sociodemographic, emotional, functional, and psychosocial factors. Age, female sex, affective symptoms, and age discrimination were associated with a higher probability of MCI, while literacy and better socioeconomic conditions showed a protective effect. Cluster analysis allowed for the identification of vulnerability profiles to guide preventive actions in high-risk contexts. Taken together, these findings support the incorporation of cognitive and mental health screening into primary care, the strengthening of interventions on healthy aging and literacy, and the design of targeted public policies to reduce inequities in cognitive health.

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