https://repository.uaeh.edu.mx/revistas/index.php/jbapr/issue/archive

**Journal of Basic and Applied Psychology Research**

*Biannual Publication, Vol. 3, No. 6 (2022) 1-8*

ISSN: 2683-2267

# Identification of depressive symptomatology in people with type II diabetes

# Identificación de sintomatología depresiva en personas con diabetes tipo II

*José F. Mora-Romo [a], Rafael A. Samaniego-Garay [b], Isauro García-Alonzo [c] y Mayra A. Chávez-Martínez [d]*

**Abstract:**

The aim of this work it's the identification of depressive symptomatology in people with type II diabetes. Among the literature, associations have been found between both, even considering depression as a possible risk identifier for developing Diabetes Mellitus. Due to this need to identify factors that affect depressive symptomatology in the population with diabetes, we sought to develop a classification model to determine which factors affect the aggravation of this psychological problem, and subsequently confirm these results using logistic regression models and cross-validation. A non-experimental cross-sectional research design was used. Using a non-probabilistic sampling by convenience, we worked with 200 people and found various factors that influenced depressive symptomatology in people with diabetes, according to the degree of depression, with negative attitudes towards oneself being a decisive factor in establishing the type of diagnosis. In this sense, for "Normal" depressive symptomatology, the most important factor was Impairment of performance; for "Mild" symptomatology, somatic alterations were observed; for "Moderate" symptomatology, sleep disturbances; and for "Severe" depressive symptomatology, the most notable somatic alterations were observed. It is argued the need to establish filters between "Normal" depressive symptomatology and those that could be an obstacle to achieve good adherence to treatment, considering contextual and biological aspects, the last in terms of brain activation.

***Keywords:***

*Depression, Type 2 Diabetes Mellitus, Health Psychology*

**Resumen:**

El presente trabajo busca identificar la sintomatología depresiva en personas con Diabetes tipo II. Entre la literatura, se ha encontrado asociaciones entre ambas, llegando incluso a considerarse a la depresión como un posible identificador de riesgo para desarrollar Diabetes Mellitus. Debido a esta necesidad de identificar factores que inciden sobre la sintomatología depresiva en la población con diabetes, se buscó elaborar un modelo de clasificación para conocer qué factores inciden en el agravamiento de este problema psicológico, y posteriormente confirmar estos resultados mediante modelos de regresión logística y validación cruzada. Se utilizó un diseño de investigación no experimental de tipo transversal. Mediante un muestreo no probabilístico por conveniencia, se trabajó con 200 personas encontrándose diversos factores que incidían sobre la sintomatología depresiva en personas con diabetes, según el grado de depresión, siendo las actitudes negativas hacia sí mismos un factor decisivo para establecer el tipo de diagnóstico. En este sentido, para la sintomatología depresiva "Normal", el factor más importante fue el Deterioro del rendimiento; para la sintomatología "Leve" se observó las Alteraciones somáticas; para la sintomatología "Moderada", las alteraciones del sueño; y para la sintomatología depresiva "Grave", se observaron las Alteraciones somáticas más notables. Se argumenta la necesidad de establecer filtros entre la sintomatología depresiva "Normal" y aquellas que pudieran resultar como un obstáculo para lograr una buena adherencia al tratamiento, considerando aspectos tanto contextuales como biológicos en términos de activación cerebral.

***Palabras Clave**:*

*Depresión, Diabetes Mellitus Tipo 2, Psicología de la Salud*

[a] Corresponding author, Universidad Autónoma de Zacatecas, https://orcid.org/0000-0002-6201-4622, Email: j_fmora@hotmail.com

[b] Universidad Autónoma de Zacatecas, https://orcid.org/0000-0002-7877-0959, Email: psicsalud@gmail.com

[c] Universidad Autónoma de Zacatecas, https://orcid.org/0000-0003-2528-3783, Email: isauro.g@uaz.edu.mx

[d] Universidad Autónoma de Coahuila, https://orcid.org/0000-0003-2427-130X, Email: mayrachavezmartinez@uadec.edu.mx

*Received: 14/05/2021, Accepted: 01/10/2021, Published: 05/01/2022*

## INTRODUCTION

In the world, 60% of deaths are caused by non-communicable diseases (Secretaría de la Salud, 2018) being in America 76% of registered deaths (Secretaría de Salud, 2018). In Mexico, Type 2 Diabetes Mellitus (T2DM) was the second leading cause of death in 2017 (Instituto Nacional de Estadística y Geografía [INEGI], 2018) and in 2020 reported an annual death rate of 8.2 per 10,000 inhabitants and an excess mortality attributed to T2DM of 35.6% attributable to the improper management of the disease caused by the SARS-CoV-2 pandemic (INEGI, 2020). In addition, it is one of the main causes of the increase in disability-adjusted life years, as people with T2DM have a 67% increased risk of developing any disability (Subsecretaría de Integración y Desarrollo del Sector Salud, 2015; Tabesh et al., 2018).

The comorbidity between T2DM and depression has been studied extensively (see e.g., Serrano et al., 2012; Castillo-Quan et al., 2010; Pineda et al., 2004; Mezuk et al., 2008; Wang et al., 2016; Graham et al., 2021). This is because this disease alone places a heavy burden on healthcare systems. In this situation, it may become common to express feelings of frustration and rejection (Serrano et al., 2012) or irritability and social isolation (Pineda et al., 2004), which will lead to poor adherence to treatment, as well as to the development of complications of the disease such as the worsening of insulin resistance because it has been reported that depression can activate the hypothalamic-pituitary-adrenal axis and the sympathoadrenal system, which would contribute to this risk (Mezuk et al., 2008). Within the North American population, the prevalence of depression has been estimated at 10.6% in people with T2DM, this being 1.56 times higher than the general population (Wang et al., 2016).

Other complications that have been associated with the presence of depression were "diabetic retinopathy, nephropathy, neuropathy, macrovascular complications, and sexual dysfunction" (Castillo-Quan et al., 2010, p. 349).

Although it has been considered that the influence between both variables may be bidirectional (Graham et al., 2021), these authors suggest that the presence of depressive symptomatology can be used to identify individuals at high risk of developing T2DM.

In this sense, Alzoubi et al. (2018) argue the importance of the implementation of psychological assessment services in primary health systems care since, even in periods of 4 years of follow-up, higher levels in HbA1c analytics have been observed in people with diabetes with depression than in patients without depression, this possibly related to the decrease in self-care behaviors that people with diabetes should follow such as healthy diets, physical activity, and medication intake.

The importance of incorporating psychological services would not only be reflected in better control of the disease but would also positively affect the quality of life of people with diabetes by providing interventions that target both depression and diabetes-related distress (Li et al., 2017).

Regarding the methodology used, works such as Khalil and Al-Jumaily (2017), offer a promising perspective for the application of Machine Learning algorithms in health psychology research where, by investigating the relation between depression and T2DM, they refer that this type of analysis can provide a great benefit by allowing a comprehensive inspection on the requirements of people regarding the health services they need, both from a palliative and preventive approach.

With this in mind, the objective of this research was to develop a classification model to determine the factors that influence depressive symptomatology in people with Type 2 Diabetes Mellitus. For this purpose, classification models were made by decision trees models using the CHAID algorithm, and then logistic regression models were carried out to confirm the results by k-folds cross-validation.

## METHOD

*Research design*: A non-experimental research design was used since there was no direct control over the independent variables (Kerlinger and Lee, 2002), and cross-sectional because the collection of information was done at a single point in time (Gonzalez, 2017).

*Participants*: Using a non-probabilistic sampling by convenience, we worked with 200 people attending institutionalized health services, of whom 87 were men and 113 women. 146 were married, 17 single and 37 divorced, from the northern part of Mexico, most of whom, at the time of the study, had been diagnosed between 37-48 months ago. Of these 200 people, 44.3% had some diabetic complication such as glaucoma, neuropathy, hypertension and renal problems, among others.

*Instrument*: The Beck depression scale (Beck and Lester, 1973), in its standarized version for the Mexican population (Jurado et al., 1998) was used to measure the degree of depressive symptomatology in people with type II Diabetes Mellitus. This scale has three factors: (1) Negative Attitudes Toward Oneself, defined by pessimism, suicidal thinking, feeling of failure, self-blame, and personal disgust, (2) Performance Impairment defined as inhibition and fatigue before work, and (3) Somatic Alterations, understood as anorexia, weight loss and sleep problems, among others. In the present study, the scale as a whole obtained a Cronbach's coefficient of .854.

*Procedure*: Instituto Mexicano de Seguridad Social (IMSS) and Instituto de Seguridad y Servicios Sociales para los Trabajadores del Estado (ISSSTE) health centers were visited with the prior consent and approval of their directors in order to apply the measurement instruments. A letter of consent to participate in the research was read to each participant and, once they had accepted the terms, they were given instructions for filling out the scales. This took between 10-15 minutes per participant.

*Data analysis*: For the study, classification models were carried out using decision tree models through the "exhaustive CHAID" algorithm and logistic regression models. Due to the low prevalence of major depressive symptomatology (consider that the risk of major depressive disorder is around 5% in the general population [De la Fuente and Heinze, 2014]), which in our study was 3%, and in order to avoid overfitting on the regression model, it was decided to perform several stages of data analysis.

First, the classification model was performed using decision trees as an exploratory analysis to determine the most important variables for predicting depressive symptomatology. The exhaustive CHAID algorithm was chosen because it allows the classification of multinomial categories, while other algorithmic options, such as CART, only work with binomial categories; therefore, it is perfectly suited for the classification of Normal, Mild, Moderate and Severe symptomatology. The exhaustive CHAID (Chi-Square Automatic Interaction Detection) algorithm uses the Chi-Square test to establish the splits between nodes and their predictor variables, correcting the multiple comparisons made in the analysis process by means of Bonferroni adjusted p-values (<.05) (Horner, 2010).

However, since the discriminative capacity of the exhaustive CHAID algorithm is limited, it was decided to carry out a second stage analysis. For this, logistic regression models were carried out. Once the non-significant independent variables were eliminated, the first analysis was performed again, resulting in a more parsimonious classification model.

It should be noted that, following Machine Learning principles, the data set of this research was randomly segmented into a training set and a test set, where 80% of the original dataset were destinated to the training set and the remain 20% to the test set. The training set was used for the learning algorithm, in other words, for the algorithm to detect the independent variables that matched the types of depressive symptomatology; while the test set was used to evaluate the number of errors made by the classification model. For this, in the test set the independent variables are administered without the dependent variables, with the algorithm being in charge of establishing them; that is, the algorithm tries to establish the appropriate category (the type of depressive symptomatology, for our case) based on the characteristics of the independent variables (Mohri et al., 2018), to then proceed to assess the accuracy of such classifications in a confusion matrix .

The decision tree classification model was developed using IBM Modeler version 18 software, while the logistic regression models were performed in RStudio Desktop 1.4.1103

## ETHICAL ASPECTS

Article 60 of the Psychologist's Code of Ethics (2007) was considered, which establishes that, when conducting research, the psychologist refrains from drawing conclusions that are not directly, objectively and clearly derived from the results obtained. In addition, based on article 138, participants were informed about the foreseeable academic uses of the information generated by their services.

Likewise, based on the code of ethical conduct of the American Psychological Association (2017), participants were informed about the objective of the research, the duration of the application of instruments and the related procedures; as well as their right to not participate and to abandon the application at the moment they consider it appropriate and to whom to turn to in case doubts were arise during the application of the instruments.

## RESULTS

*Descriptive results*

The results of the sociodemographic characteristics collected show that, in general, the population under study had a mean age of 57 years, of which 77 are men and 104 women, most are married (70%), with a high school education (25%), housewife (34%), residents of Saltillo (79.5%), with a time of diagnosis of 49 months or more (54.5%) who do not present diabetic complications (46.5%).

The majority do not report the need for a caregiver (76%), while those who do require a caregiver are supported by family members (10%). Eighty-four percent of the participants had monthly medical check-ups through health services such as IMSS (66.5%) and ISSSTE (12.5%).

*Exploratory classification analysis*

The decision tree model was performed with the sociodemographic variables, the 21 items of the Beck depression scale, as well as the scores of the three dimensions of the scale mentioned above. This was to determine whether any of these variables had an influence on the type of depressive symptomatology (Normal, Mild, Moderate or Severe).

In this first analysis, seven predictor variables were obtained, shown in Table 1:

**Table 1**
*Importance of variables*

| Predictor variable | Variable significance |
|---|---|
| Negative Attitudes Toward Oneself | 0.46 |
| Somatic Alterations | 0.24 |
| Performance Impairment | 0.18 |
| Interest in others (BDI 12) | 0.07 |
| Satisfaction (BDI 4) | 0.03 |
| Sleep alterations (BDI 16) | 0.01 |
| Appetite alterations (BDI 18) | 0.01 |

Due to the length of this first classification tree, we will not delve into its details and will instead report its classification performance.

With seven predictor variables, the model was able to perform 93.12% correct classifications with the training dataset and 90% correct predictions with the test set, which gives us information about a good predictive ability. The confusion matrices for both the training set (Table 2) and test set (Table 3) are shown below:

**Table 2**
*Training set confusion matrix*

| | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 55% | 1.25% | | |
| Mild | 1.25% | 21.87% | 2.5% | |
| Moderate | | 1.25% | 14.37% | |
| Severe | | | 0.62% | 1.87% |

**Table 3**
*Testing set confusion matrix*

| | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 67.5% | 2.5% | | |
| Mild | | 17.5% | 2.5% | |
| Moderate | | | 5% | |
| Severe | | | 5% | |

*Confirmatory analysis*

Logistic regression models were performed to confirm the influence of the variables obtained from the classification model. The first model (Table 4) shows three model fit parameters (AIC = 96.77, BIC = 123.81, LogLik = -39.38) as well as the Nagelkerke's standardized version of the $R^2$ = 0.89 which implies a high coefficient of determination.

As can be seen, there are variables that do not represent a statistically significant influence, so a backward elimination was performed by eliminating those variables with higher p-values in a descending order, obtaining a final model of four predictor variables (Table 5).

By eliminating the Interest in Others, Appetite alteration and Satisfaction variables, not only a more parsimonious regression model was obtained, but the fit statistics improved (AIC= 94.58 and BIC=112.61) with a slight exception of LogLik and Nagelkerke's $R^2$. However, as will be seen below, this did not lead to any drop in performance in both the cross-validation and the classification model.

In terms of greater influence, it is observed that for each additional point obtained in the factor of Negative attitudes towards oneself, participants would be 1.55 times more likely to present greater depressive symptoms. Following this, each point obtained in the Somatic Alterations factor represents that 1.26 times more probability of the development of depressive symptoms will be obtained. Then, depressive symptomatology is 1.13 times more likely to be present by every point obtained on Performance impairment; and finally, it was observed that sleep disturbances increase the probability by 1.1 times.

With this, the model suggests that the factor with the greatest importance in the prediction of depressive symptomatology is Negative attitudes towards oneself, followed by Somatic alterations, Performance impairment and finally Sleep alterations.

To verify this, a cross-validation with 10 iterations (k-folds cross-validation) was carried out with both models (Table 6) where it was verified that in the final model the RMSE and MAE parameters decreased, while the $R^2$ increased slightly.

**Table 6**
*10-iterations Cross-validation*

| Initial model | | | Final model | | |
|---|---|---|---|---|---|
| RMSE | $R^2$ | MAE | RMSE | $R^2$ | MAE |
| .343 | .863 | .274 | .335 | .870 | .269 |

*Final classification model*

For this new classification model, the variables mentioned in Table 7 were used.

**Table 7**
*Importance of variables*

| Predictor variable | Importance of the variable |
|---|---|
| Negative attitudes toward oneself (NATO) | 0.52 |
| Somatic alterations (SA) | 0.30 |
| Performance impairment (PI) | 0.18 |
| Sleep alterations (BDI 16) | 0.07 |

As can be seen in Figure 1, the first division refers to Normal symptomatology (node 1) which assumes that it can be predicted by scores < = 2 on the NATO factor ($X^2$ = 156.5). Node 5 shows us that this type of scores, in conjunction with scores < = 2 in PI and reports in sleep alterations, can increase depressive symptomatology, reaching Mild symptoms.

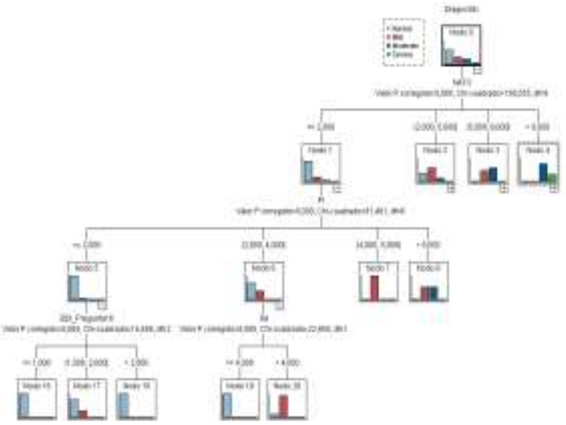

Figure 1 Normal depressive symptomatology breakdown

Nodes 6, 7 and 8 show that as more PI is reported, symptomatology increases, even reaching Moderate symptoms (see Node 8). For its part, the SA influences the report of Normal symptoms to increase to Moderate symptoms (node 20; $X^2 = 22.95$).

Regarding mild symptomatology (node 2), it is observed that scores between 2-5 in NATO influence more people to be placed in this category (Figure 2).

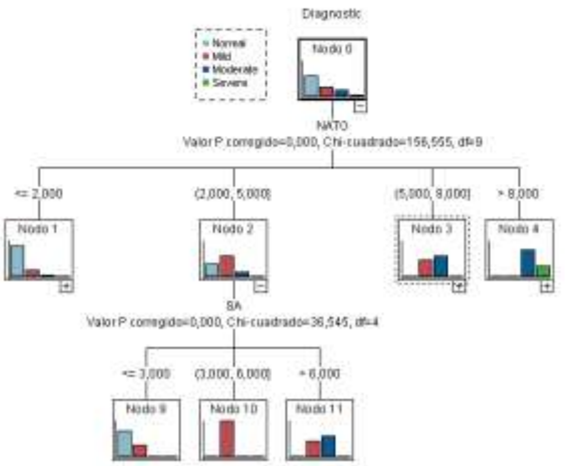


Figure 2 Mild symptomatology breakdown

What will determine the type of symptoms will be the SA ($X^2 = 36.54$), showing how, together with a higher score in this factor, one can go from experiencing Normal (node 9), Mild (node 10) to Moderate (node 11) symptomatology.

Turning now to node 3 (Figure 3)with a higher prevalence of moderate symptoms, it is observed how Sleep alterations influences the presence of these symptoms ($X^2 = 8.905$) since only a score >1 is enough for this.

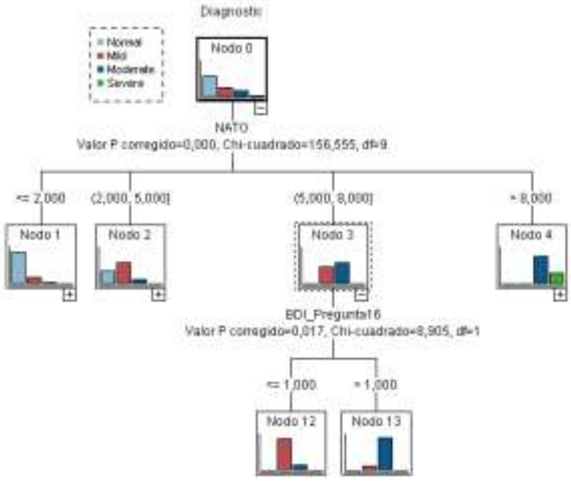


Figure 3 Moderate symptomatology breakdown

Finally, node 4 shows that high scores (>8) on the SA factor ($X^2 = 8.905$) are decisive for the diagnosis of severe depressive symptomatology in the sample studied.

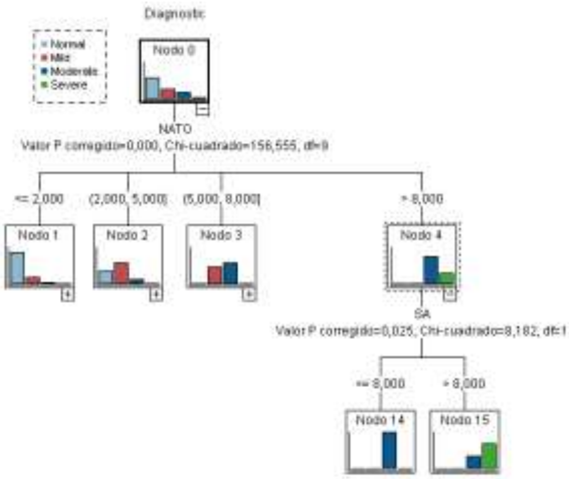


Figure 4 Severe symptomatology breakdown

Regarding the performance of the classification model, with four predictor variables, the model was able to perform 90.62% of correct classifications with the training data set and 92.5% of correct predictions with the test set, which provides us with information about a better predictive capacity with respect to the initial model with an increase in accuracy of 2.5% and with a more parsimonious configuration by having only four of the seven initial variables. The confusion matrices for both the training set (Table 8) and the test set (Table 9) are shown below:

**Table 8**

*Training set confusion Matrix*

| | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 55.62% | .625% | | |
| Mild | 3.75% | 19.3% | 2.5% | |
| Moderate | | 1.25% | 13.12% | 1.25% |
| Severe | | | | 2.5% |

**Table 9**

*Testing set confusion Matrix*

| | Normal | Mild | Moderate | Severe |
|---|---|---|---|---|
| Normal | 67.5% | 2.5% | | |
| Mild | 2.5% | 15% | 2.5% | |
| Moderate | | | 5% | |
| Severe | | | | 5% |

## DISCUSSION

In the present work we sought to establish a classification model for the prediction of depressive symptomatology in people with type 2 Diabetes Mellitus by decision trees model. This study approach has allowed us to know not only which variables influence the depresive symptomatology, as would have been the case with a regression model, but to know in a more comprehensive way how these variables interact with each other with depressive symptoms, which allows us to make a better diagnosis and monitoring of this problem for the benefit of the prognosis of the T2DM disease (Owens-Gary et al., 2019). In these cases, where aspects such as negative thoughts, attitudes and beliefs interfere with self-care behaviors to improve disease control, cognitive-behavioral interventions have been found to be appropriate to overcome them (Li et al., 2017), pointing out the relevance of the implementation of psychological in the care systems.

The identification of factors that promotes depressive symptomatology that we found is in agreement with the results of Asuzu et al. (2018) who argued the importance of orienting psychological services not only to the disorder as such, but to manage depressive symptoms to avoid reach a threshold. For example, we observed how, the factor of Negative Attitudes Toward Oneself, was the most important in establishing the diagnosis of depression. This may be due to aspects such as physical inactivity, poor body perception due to obesity, inability to perform work and daily activities as they did before the disease and the evaluation made of one's own health (Diderichsen and Andersen, 2019).

Regarding Normal depressive symptomatology, aspects such as somatic alterations and sleep alterations, have incidence for symptomatological aggravation, reaching Mild symptoms when people with MD report performance impairment.

Regarding mild symptomatology, it was observed that factors such as somatic alterations in medium degree (≤ 6 points on the Beck scale) could lead to increase symptomatology to a moderate degree. This raises the importance of working to prevent diabetic comorbidities that affect functional aspects of the patients, such as visual impairment or fatigue.

Moderate symptomatology was observed to be influenced by the reactive sleep alterations, which highlights the need for stable strategies aimed at sleep hygiene, since this would influence the reduction of symptoms such as fatigue in this population.

And finally, it was observed that severe depressive symptomatology is influenced by somatic alterations with great repercussions on the patient (scores > 8 on the Beck depression scale), so that, although previously, when speaking of mild symptomatology, the importance of preventing diabetic comorbidities was mentioned, these scores could indicate that it is now a question of reducing or directly treating these comorbidities.

This exhaustive data analysis becomes relevant when pointing out the results reported by Graham et al., (2020), where depressive symptoms are associated with increased risk of T2DM. Hence the need to establish filters between "Normal" depressive symptomatology and those that could result as an obstacle to achieve good adherence to treatment, both considering contextual (Khan, 2019) and biological aspects in terms of brain activation (Wang et al., 2020).

In turn, the Machine Learning assumptions have allowed us to test the model designed by using training and test sets. This is relevant because once the structure of the classification model has been established using training data, it is tested using "new data" where the algorithm used is responsible for establishing the diagnosis using the selected independent variables (in our case, the type of symptomatology using the factors of the Beck depression scale). This is an advantage since, apart from the statistical validation of the model fit parameters, p-values and cross-validation (see Table 5 and Table 6), it allows us to validate our model through the accuracy parameter by means of confusion matrices (see Table 8 and Table 9).

## REFERENCES

Alzoubi, A., Abunaser, R., Khassawneh, A., Alfaqih, M., Khasawneh, A. & Abdo, N. (2018). The bidirectional relationship between diabetes and depression: a literature review. *Korean Journal of Family Medicine, 39*(3), 137-146. https://dx.doi.org/10.4082%2Fkjfm.2018.39.3.137.

American Psychological Association. (2017). *Ethical principles of psychologist and code of conduct.*

Recuperado de: https://www.apa.org/ethics/code/ethics-code-2017.pdf.

Asuzu, C., Walker, R., Strom, J. & Egede, L., (2017). Pathways for the relationship between diabetes distress depression, fatalism and glycemic control in adults with type 2 diabetes. *Journal of Diabetes and its Complications, 31*(1), 169-174. https://dx.doi.org/10.1016%2Fj.jdiacomp.2016.09.013.

Beck, A. & Lester, D. (1973). Components of depression in attempted suicides. *The Journal of Psychology: Interdisciplinary and Applied, 85*, 257-260.

Castillo-Quan, J., Barrera-Buenfil, D., Pérez-Osorio, J. & Álvarez-Cervera, F. (2010). Depresión y diabetes: de la epidemiología a la neurobiología. *Revista de Neurología, 51*(6), 347-359.

De la Fuente, J. & Heinze, G. (2014). *Salud mental y medicina psicológica*. McGraw Hill.

Diderichsen, F. & Andersen, I. (2019). The syndemics of diabetes and depression in Brazil – An epidemiological analysis. *SSM – Population Health, 7*. https://dx.doi.org/10.1016%2Fj.ssmph.2018.11.002.

González, F., Escoto, M. & Chávez, J. (2017). *Estadística aplicada en psicología y ciencias de la salud*. Manual Moderno.

Graham, E., Deschenes, S., Khalil, M., Danna, S., Filion, K. & Schmitz, N. (2020). Measures of depression and risk of type 2 diabetes: A systematic review and meta-analysis. *Journal of Affective disorders, 265*, 224-232. https://doi.org/10.1016/j.jad.2020.01.053.

Graham, E., Deschenes, S., Rosella, L. & Schmitz, N. (2021). Measures of depression and incident type 2 diabetes in a community sample. *Annals of Epidemiology, 55*, 4-9. https://doi.org/10.1016/j.annepidem.2020.11.010.

Horner, S., Fireman, G. & Wang, E. (2010). The relation of student behavior, peer status, race, and gender to decisions about school discipline using CHAID decision trees and regression modeling. *Journal of School Psychology, 48*, 135-161.

Instituto Nacional de Estadística y Geografía. (2018). *Características de las defunciones registradas en México durante 2017.* https://www.inegi.org.mx/contenidos/saladeprensa/boletines/2018/EstSociodemo/DEFUNCIONES2017.pdf

Instituto Nacional de Estadística y Geografía. (2020). Características de las defunciones registradas en México durante enero a agosto de 2020. https://www.inegi.org.mx/contenidos/saladeprensa/boletines/2021/EstSociodemo/DefuncionesRegistradas2020_Pnles.pdf.

Jurado, S., Villegas, M., Méndez, L., Rodríguez, F., Loperena, V. & Varela, R. (1998). La estandarización del inventario de depresión de Beck para los residentes de la ciudad de México. *Salud Mental, 21*(3), 26-31.

Kerlinger, F. & Lee, H. (2002). *Investigación del comportamiento. Métodos de investigación en ciencias sociales.* McGraw-Hill.

Khan, Z. (2019). Prevalence of Depression and Associated Factors among Diabetic Patients in an Outpatient Diabetes Clinic. *Psychiatry Journal, 2019*. https://doi.org/10.1155/2019/2083196.

Li, C., Xu., D., Hu, M., Tan, Y., Zhang, P., Li, G. & Chen, L. (2017). A systematic review and meta-analysis of randomized controlled trials of cognitive behavior therapy for patients with diabetes and depression. *Journal of Psychosomatic Research, 95*, 44-54. https://doi.org/10.1016/j.jpsychores.2017.02.006.

Mezuk, B., Albrecht, S., Eaton, W. & Hill, S. (2008). Depression and Type 2 Diabetes Over the Lifespan: a meta-analysis. *Diabetes Care, 31*(12), 2383-2390. https://doi.org/10.2337/dc08-0985.

Mohri, M., Rostamizadeh, A. & Talwalkar, A. (2018). *Foundations of machine learning.* The MIT Press.

Owens-Gary, M., Zhang, X., Jawanda, S., McKeever, K., Allweiss, P. & Smith, B. (2018). The Importance of Addressing Depression and Diabetes Distress in Adults with Type 2 Diabetes. *Journal of General Internal Medicine, 34*, 320-323. https://doi.org/10.1007/s11606-018-4705-2.

Pineda, N., Bermúdez, V., Cano, C., Mengual, E., Romero, J., Medina, M., Leal, E., Rojas, J. & Toledo, A. (2004). Niveles de Depresión y Sintomatología característica en pacientes adultos con Diabetes Mellitus tipo 2. *Archivos Venezolanos de Farmacología y Terapéutica, 23*(1). http://ve.scielo.org/scielo.php?pid=S0798-02642004000100013&script=sci_arttext.

Secretaría de Salud (2018). *Transición epidemiológica.* http://187.191.75.115/gobmx/salud/documentos/transicion/transicion_epidemiologica_2018.pdf.

Serrano, C., Zamora, K., Navarro, M. & Villarreal, E. (2012). Comorbilidad entre depresión y diabetes mellitus. *Medicina Interna de México 28*(4), 325-328.

https://www.medigraphic.com/pdfs/medintmex/mim-2012/mim124d.pdf.

Sociedad Mexicana de Psicología. (2007). *Código ético del psicólogo*. México, D.F: Trillas.

Subsecretaría de Integración y Desarrollo del Sector Salud (2015). *Informe sobre la salud de los mexicanos 2015: Diagnóstico general de la salud poblacional*. https://www.gob.mx/cms/uploads/attachment/file/64176/INFORME_LA_SALUD_DE_LOS_MEXICANOS_2015_S.pdf.

Tabesh, M., Shaw, J., Zimmet, P., Söderberg, S., Koye, D., Kowlessur, S., Timol, M., Joonas, N., Sorefan, A., Gayan, P., Alberti, K., Toumilehto, J. & Magliano, D. (2018). Association between type 2 diabetes mellitus and disability: what is the contribution of diabetes risk factors and diabetes complications? *Journal of Diabetes, 10*(9), 744-752. https://doi.org/10.1111/1753-0407.12659.

Wang, D., Wang, H., Gao, H., Zhang, H., Zhang, H., Wang, Q. & Sun, Z. (2020). P2X7 receptor mediates NLRP3 inflammasome activation in depression and diabetes. *Cell & Bioscience, 10*(28). https://doi.org/10.1186/s13578-020-00388-1.

Wang, Y., Lopez, J., Bolge, S., Zhu, V. & Stang, P. (2016). Depression among people with type 2 diabetes mellitus, US National Health and Nutrition Examination Survey (NHANES), 2005–2012. *BMC Psychiatry, 16*(88). https://doi.org/10.1186/s12888-016-0800-2.

Table 4
*First logistic regression model*

| | AIC | BIC | LogLik | Nagelkerke $R^2$ | B | E.S. | Wald | Odd Rattio |
|---|---|---|---|---|---|---|---|---|
| Model | 96.77 | 123.81 | -39.38 | 0.8905 | | | | |
| Intercept | | | | | 1.59** | 0.26 | | 4.93 |
| Satisfaction | | | | | .05 | .033 | 2.46 | 1.05 |
| Interest in others | | | | | .02 | .033 | 0.46 | 1.02 |
| Appetite | | | | | .03 | .033 | 1.21 | 1.03 |
| Sleep alterations | | | | | .1** | .034 | 8.23** | 1.1 |
| Negative attitudes toward oneself | | | | | .43*** | .035 | 148.81*** | 1.54 |
| Performance impairment | | | | | .08 | .45 | 3.33 | 1.08 |
| Somatic alterations | | | | | .2*** | .45 | 20.68** | 1.23 |

**p<.05 **p<.01 ***p<.001*

Table 5
*Final logistic regression model*

| | AIC | BIC | LogLik | Nagelkerke $R^2$ | B | E.S. | Wald | Odd Rattio |
|---|---|---|---|---|---|---|---|---|
| Model | 94.58 | 112.61 | -41.29 | .8875 | | | | |
| Intercept | | | | | 1.59** | 0.026 | | 4.93 |
| Sleep | | | | | 0.09** | 0.034 | 8.08** | 1.1 |
| Negative attitudes toward oneself | | | | | 0.43*** | 0.035 | 151.61*** | 1.55 |
| Performance impairment | | | | | 0.12** | 0.038 | 10.62** | 1.13 |
| Somatic alterations | | | | | 0.23*** | 0.4 | 33.13*** | 1.26 |

**p<.05 **p<.01 ***p<.001*