Using ecological momentary assessment and machine learning techniques to predict depressive symptoms in emerging adults

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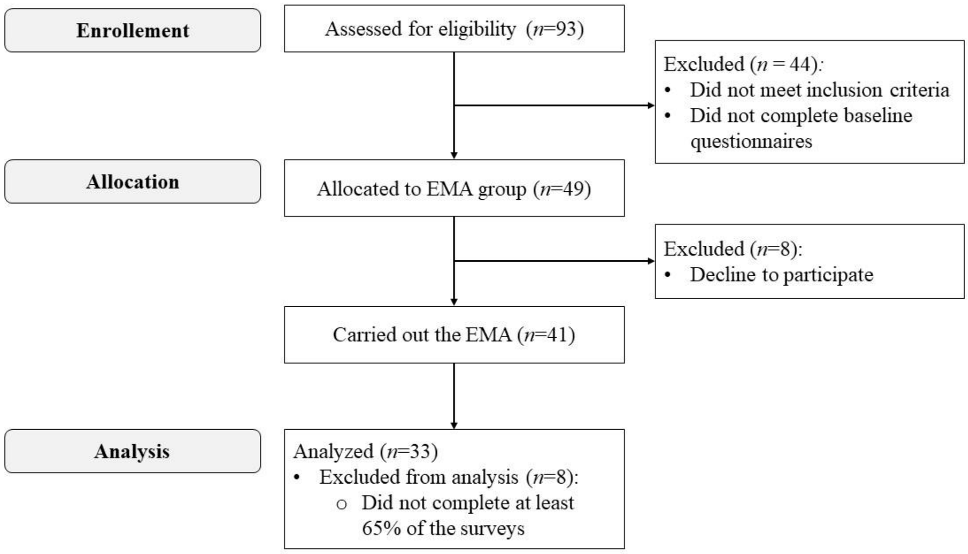

Abstract

The objective of this study was to predict the level of depressive symptoms in emerging adults by analyzing sociodemographic variables, affect, and emotion regulation strategies. Participants were 33 emerging adults (*M*=24.43; *SD*=2.80; 56.3% women). They were asked to assess their current emotional state (positive or negative affect), recent events that may relate to that state, and emotion regulation strategies through ecological momentary assessment. Participants were prompted randomly by an app 6 times per day between 10 am and 10 pm for a seven-day period. They answered 1233 of the 2058 surveys (beeps), collectively. The analysis of observations, using Machine Learning (ML) techniques, showed that the Random Forest algorithm yields significantly better predictions than other models. The algorithm used 13 out of the 36 variables adopted in the study. Furthermore, the study revealed that age, emotion of worried and a specific emotion regulation strategy related to social exchange were the most accurate predictors of severe depressive symptoms. By carefully selecting predictors and utilizing appropriate sorting techniques, these findings may provide valuable supplementary information to traditional diagnostic methods and psychological assessments

Keywords: emerging adults, emotional regulation strategies, positive and negative affect, depressive symptoms, ecological momentary assessment (EMA), machine learning techniques

1. Introduction

1.1. Depressive symptoms in emerging adults

Emerging adults are individuals between the ages of 18 and 29 (Arnett, 2014). This stage is considered to be the period between the end of adolescence and the assumption of adult responsibilities, such as securing stable job, getting marriage or becomih a parent. Arnett and Tanner (2006) have described the emerging adulthood as a time of identity exploration, instability, self-focus, possibilities and as a period of feeling in-between. The development period can be stressful time due to the need to adapt to many changes and potentially harmful situations (Osma et al., 2021). This stress may impact in the psychological status of this group and even increase the incidence of mental disorders (Cooke et al., 2006). Emerging adults may be considered at risk of developing or worsening psychopathology (Bernstein et al., 2021).

Depression is a common mental disorder and it is estimated that 5% of adults worldwide suffer from depression (WHO, 2023). In fact, anxiety and depressive disorders are the most frequent ones for which patients seek care in public health settings (Osma et al., 2022). The transition from adolescence to adulthood has seen a significant increase in depression, making it a major public health concern (Gomez-Baya et al., 2022). Vieta et al. (2021) found that the annual incidence rate of diagnosed depressive disorders is 7–8 cases/1000 persons/year. Beyond the diagnosis of depression, subclinical symptoms of depression can also contribute to increased distress levels in young individuals and elevate the risk of developing psychopathology and suicidal behavior in the future (Balázs et al., 2013; Jinnin et al., 2017).

The emergence of depressive symptoms, and going further, the onset of depression, is the result of a complex interaction of social, psychological, and biological factors (WHO, 2023). Socio-demographic variables, such as gender and age, are related to depressive symptoms. Women tend to have higher levels of depression and there is a higher prevalence of depression in adulthood than in childhood or older age (WHO, 2023). Among the emotional variables, affect and emotion regulation appear to be closely related to depression (Aldo et al., 2010). However, more research is needed to better understand the dinamics of regulation and how people cope with their emotions in daily life (Burr & Smanez-Larkin, 2020).

1.2. Affect and emotion regulation strategies

According to the bidimensional model, affective structure comprises of two independent dimensions: positive and negative affect (Watson & Tellegen, 1985). Positive affect reflects the extent to which a person feels enthusiastic, active and satisfied, while negative affect is a general dimension of subjective distress and unpleasurable mood that includes anger, fear and nervousness (Watson et al., 1988). Cross-sectional studies have provided empirical support for this model (e.g., Sanmartín et al., 2018). However, to examine affect as a dynamic process, intensive longitudinal studies such as ecological momentary assessment are needed (Brose et al., 2020). A multilevel approach has shown the relationship between affective dimensions and depressive symptoms in young adults (Cooke et al., 2022).

Emotional regulation strategies are associated with positive and negative affect in ecological momentary assessment studies (Boemo et al., 2022) and the way people regulate their emotions in everyday life may have important effects on their health (Lee & Choi, 2023).

Emotion regulation (ER) refers to intrinsic and extrinsic processes that control the initiation, maintenance and modification of positive and negative emotional reactions, through various processes that will also influence the latency, intensity, and duration of such emotion (Gross et al., 2011). One of the most widely used models of emotion regulation is Gross's model (Gross, 1999; 2014). This model proposes that emotion may be studied in terms of where the regulation strategy fits within the phases of emotional generation (situation, attention, interpretation and response).

Some of the most relevant emotion regulation strategies that have been analysed in meta-analyses are problem-solving, distraction, rumination, positive reappraisal, acceptance and emotional suppression (Boemo et al., 2022). Problem-solving refers to the use of active strategies or plans to make changes in the situation and is included in the situation modification phase. Distraction (directing attention to something other than emotions) and rumination (constantly thinking about how I feel) are two emotion regulation strategies that are part of the attention-directing phase. In the phase of interpretation or cognitive change, two regulation strategies are positive reappraisal (looking at things from a more positive perspective) and acceptance (trying to accept the situation and the emotions). Finally, in response modulation phase, two of the emotion regulation strategies would be emotional suppression (keeping emotions to oneself) and social sharing (sharing emotions with other people) (Bucich & MacCann, 2019; Gross, 1999). Sharing emotions with others is a common occurrence in daily life (Rimé et al., 2020). This sharing of emotions is not dependent on emotional valence (Berger, 2011), and the intensity of the emotions experienced is positively correlated with the likelihood of sharing (Rimé, 2009). However, it is important to note that recounting an emotion can often lead to emotional reactivation rather than emotional discharge (Rimé, 2009). According to Choi and Toma (2014), sharing emotions has been shown to amplify the emotional tone of triggering events, increasing the positive affect generated by a positive event, but also the negative affect generated by a negative event.

Usually, ER strategies have been categorized as commonly adaptive or maladaptive. Maladaptive strategies such as rumination, avoidance or suppression are associated with more psychopathology and adaptive strategies such as acceptance, reappraisal or problem solving are associated with less psychopathology (Aldo et al., 2010). However, recently it has been proposed that this is a simplistic view and that adjustment may imply the implementation of ER strategies variably to meet contextual demands (Blanke et al., 2020; Boemo et al., 2022). It is necessary to deepen the functioning of emotion regulation strategies in everyday life, especially those related to depressive symptoms, in order to improve early identification of vulnerable profiles and prevent depression in emerging adulthood (Liu et al., 2017; Sauer-Zavala et al., 2021).

1.2. Ecological momentary assessment

Internalizing disorders, such as depressive symptoms, are often assessed with retrospective self-report questionnaires, which are highly informative in capturing the perceived frequency and intensity of symptoms (Clark & Watson, 2019). Retrospective questionnaires cannot measure symptoms as they occur in real time, but instead rely on recollections of past experiences to provide a summary of symptoms over a given period (Jimenez et al., 2022).

Ecological momentary assessment (EMA) refers to a method of data collection that attempts to capture respondents' activities, emotions, and thoughts in the moment in their natural environment. It typically uses prompts administered through a personal electronic device. EMA generally involves prompting respondents to answer a series of questions about their behavior, thoughts or emotions (McDevitt-Murphy, 2018; Piot et al., 2022) trying to quantify people's momentary behavior, thoughts, feelings, and context as they unfold in daily life (Bolger et al., 2003).

In many areas of psychology and related disciplines, there has been an increase in the prevalence of research using EMA in recent years (Boemo et al., 2022; Liao et al., 2016)**,** which is "a method of collecting real-time data based on repeated measures and observations that take place in the participant's daily environment" (Degroote et al., 2020). It is conducted using mobile technology to collect data from participants in their natural environment (the 'ecological' aspect) at random moments (the 'momentary' aspect) throughout the day (McDevitt-Murphy et al., 2018).

The application of Machine Learning (ML) technology may be useful in detecting mental disorders (Sau & Bhakta, 2019). Orrù et al. (2020) enfazised that a machine learning approach may produce more unbiased results for psychological assessment when implemented appropriately.

1.3. The current study

To the best of our knowledge, there is limited research that combines sociodemographic and emotional variables that has been assessed ecologically and momentarily to predict de depressive symptoms in emerging adulthood. Furthermore, there is even less research that applies ML techniques to analyze such data. The aim of this study was to predict the level of depressive symptoms in emerging adults by analyzing sociodemographic variables, affect, and emotion regulation strategies. In this sense, the study is based on three hypotheses:

- Hypothesis 1. Positive affect and negative affect will predict the level of depressive symptoms negatively and positively, respectively.
- Hypothesis 2. The use of the emotion regulation strategies of rumination, suppression and distraction will be associated with higher levels of depressive symptoms; whereas the use of problem-solving, positive reappraisal, acceptance and social sharing strategies will be associated with lower levels of depressive symptoms.
- Hypothesis 3 Age and gender will predict the level of depressive symptoms, with women and older people having the highest levels.

To meet the aforementioned objectives, data mining techniques and, more specifically, machine learning (ML) will be used to predict and analyse the relationship between affective variables, ER and sociological variables and the prediction of the level of depressive symptoms in young people. In this respect, the works of Sau & Bhakta (2019) emphasize the importance of the application of Machine Learning (ML) technology in the field of automated screening for mental health illness. Along with predict quality, models deliver additional tools to understand the problem. The use of ML algorithms allows to obtain the var, after calibration, ae relevant when determining the individuals who present depressive symptoms and those who do not.

2. Methods

2.1. Participants

There were 93 people interested in participating in the research, but only 49 were included in the study (Figure 1). The final sample consisted of 33 emerging adults aged 18-29 years (*M*=24.03; *SD*=2.57; 56.3% women). The majority of participants (90.6%) were born in Spain and 9.4% were born in France, Chile or Romania. Those born in other countries had been living in Spain for 15-20 years (*M*=17.50; *SD*= 2.08). Of the emerging adults who were students (54.45%), 25% were studying for a university degree, 15.6% for a master's degree, 9.4% for a doctorate and 6.3% for an intermediate or higher level of education. Of the total number of participants, 40.6% were employed. Regarding physical health, 62.5% of the emerging adults indicated that they did not suffer or had suffered from any type of illness. Regarding mental health, 84.4% of the emerging adults indicated that they do not suffer or have suffered from any type of mental disorder.

The inclusion criteria for this study were to be an emerging adult (from 18 to 29 years old), to be a resident in any Spanish community, to have an Android Smartphone and to sign the informed consent. Participants who did not respond to at least 65% of the surveys were removed from the final sample.

-- Insert Figure 1--

2.2 Instruments

At baseline, socio-demographic variables and affective symptomatology were assessed.

Related to the *Socio-demographic variables*, an ad hoc questionnaire was used to assess gender, age, country of birth, educational level, employment, presence of physical illness and presence of mental illness.

For the *Affective symptomatology*, the instrument used was the Depression, Anxiety and Stress Scale (DASS-21; Lovibond & Lovibond, 1995). The Spanish adaptation (Daza et al., 2002) was used to assess the affective symptoms of participants during the previous week. The scale is composed of 21 items with a 4-point Likert scale (0 = *never* to 3= *almost always*). The instrument evaluates three subscales: Depression (e.g., “I was unable to become enthusiastic about anything”), Anxiety (e.g., “I felt scared without any good reason”), and Stress (e.g. “I found it difficult to relax”). Previous studies indicated adequate psychometric properties in Spanish samples (α between .73 and .81) (Fonseca-Pedrero et al., 2010). Only the depressive symptoms dimension is included in the current study.

2.3. EMA

Following the recommendations of Liao et al. (2016) and Van Roekel et al. (2019) for reporting EMA methodology areas, the training for participants, sampling and measures, schedule, item selection, prompting strategy, response and compliance, incentives and software and hardware are detailed below.

2.3.1. Training or instructions for participants

One of the most important keys to obtaining reliable data is to instruct participants on how to participate in an EMA study. Therefore, an important pre-requisite of a high compliance rate is the comprehensibility of the EMA protocol (Degroote et al., 2020).

Before the study began, participants were given a video on how to download and use the application, a document with detailed information on what each question actually meant (with pictures and examples) and how to answer it, and a Frequently Asked Questions (FAQ) document. The institutional mail from one member of the research team to whom participants could send questions was also provided.

Regarding whether and under which circumstances participants were contacted, it should be said that at mid-term of the study participants were asked to report errors related to the operational aspects of the app.

2.3.2. Sampling and measures

Contingent signal sampling was used, whereby participants provided self-assessments after receiving a random notification on their phones. Participants were expected to provide self-reports after receiving push notifications over a 7-day period. On average, participants took approximately 113 seconds to respond to each survey.

2.3.3. Schedule

All participants completed a one week of EMA receiving prompts 6 times per day assessing current emotional state, recently experienced events and emotion regulation strategies applied. Participants were notified randomly 6 times a day for 7 days during the hours of 10 AM to 10 PM. The monitoring period starting in June the 16th and finishing in June the 22nd in 2022.

2.3.4. Item selection

The total number of items per assessment were 32. The items had closed format and the answer scales used were Likert ones with continuous answers. The selected items evaluated 4 variables: context, affect, recents events that may relate to the emotion and emotion regulation strategies:

- *Contextual items.* Two close questions with multiple options where included (what are you doing at the moment and with whom).
- *Affect items.* Participants were asked about their current state (in-the-moment). Momentary assessment of affect was based on the PANAS (Watson et al., 1988; Sandín et al., 1999). It included 8 items, 4 for positive affect and 4 for negative affect in response to the question "How much you feel each of these emotions right now?". At each random prompt, participants were asked to report on how they currently felt from 1 to 5 (1= *nothing or very slightly* to 5= *very much*).

- *Recents events that may relate to the emotion.* Participants were asked whether they thought that state was related to family members, partner relationship, friends, food, health, exercise, spirituality, work, studies, travel, sleep, finances, self-esteem, body, with theirself/or other recent issues. The question about their current emotional state was: “What do you think it is related to?”.
- *Emotion Regulation (ER) strategies.* At each signal, participants were asked about the use of any ER strategies since the last beep, e.g. “How much have you done this…” using a Likert-type scale ranging from 1 (*Almost nothing*) to 5 (*A lot*). The assessment included 21 items link to the seven ER strategies: problem solving, distraction, reappraisal, rumination, acceptance, suppression, and social sharing (Bucich & MacCann, 2019; Gross, 1999).

2.3.5. Prompting strategy

This study also examined the impact of prompt frequency and latency (time from prompt signal to response) on data collection:

- *Prompt frequency.* Participants received push notifications (6 prompts/day) delivered between 10:00 AM and 10:00 PM during 7 days. Prompts were sent randomly within 6 time ranges.
- *Latency*. Latency refers to the amount of time from prompt signal to answering of prompt. Each survey was available for the next 45 minutes after the prompt. If the person did not answer it in that period time, he or she could no longer complete it. If a person left a battery unanswered (or several), it was not removed from the process.

2.3.6. Response and compliance

Compliance is one important quality marker for EMA studies. When it comes to designing a study, the number of assessments may impact the burden on participants (Hufford, 2007; Wen et al., 2017). Participants were expected to respond to at least 65% of the surveys. Of the 33 participants, 17 (51.5%) of them completed more than 90% of the surveys, 14 (42.4%) participants completed between 70% and 89% and only 2 (6.1%) people completed between 66% and 69%.

2.3.7. Incentives

Due to the fact that providing any kind of monetary or other incentive has been associated with higher compliance rates compared with no incentive, most EMA studies provide financial incentives (Wrzus & Neubauer, 2022). In this study, monetary compensation was given to participants with, at least, 65% overall response rate.

2.3.8. Software and Hardware

For the administration of the EMA, participants were only required to have a device running Android 8.0 or higher. The choice of a device with this operating system is motivated by the wide distribution of this operating system among smartphones, which are the most appropriate for carrying out the EMA at different times and places. In Spain, Android is the operating system used on 78.48% of smartphones (Statcounter GlobalStats, 2023), while worldwide Android is the operating system installed on 72.26% of smartphones.

For these devices, an application has been developed for the experiment that presents the different questions in a simple and easy way. The application itself sends notifications to users at the moments established in the design of the experiment. The information collected, along with other data such as the day/time or the time taken to answer the questions, is stored anonymously on a remote server.

2.4. Procedure

The study was advertised through social media, email and instant messaging, and people interested in taking part sent their contact details. Of the 93 people who showed interest in participating, the first 50 people were sent informed consent and the baseline survey. They were given three days to sign the informed consent and respond to the baseline survey. If there was no response, the initial survey was sent to the next person on the list. In the end, 49 people were included in the study. After completing the initial survey, the procedure for the EMA was explained to them. Participants answered a short survey 6 times a day for 7 days. The study was approved by the ethics committee of the university (code UV-INV_ETICA-2076501) and was conducted in accordance with the recommendations of the Helsinki Declaration (World Medical Association, 2013).

2.5. Data preparation

As has been previously commented, participants have answered 1266 surveys. However, some of them lack social information or have not answered all the questions. These amount to a total of 33 samples with missing values. Because they belong to the majority class (labelled as 1), we removed them from the input samples before proceeding with the model's training. In this way, we finally had 1233 labelled samples to train the model. Participants completed the Depression Anxiety and Stress Scale-21 (DASS-21) using a 3-point Likert scale to indicate the severity of their depressive symptoms. The sum of the seven items corresponding to the 'Depression' subscale was calculated. Participants were then classified into one of five categories (labels) based on their symptom severity, ranging from 1 (no depressive symptoms) to 5 (severe depressive symptoms), using the cut-off points proposed by the authors (Lovibond & Lovibond, 1995).

The variables that are used as predictors include 7 attributes that contain social and personal information (age, gender, country, level of studies, job, physical illness, and mental disorder) and 32 attributes that contain the answers of the individuals to the questionary that follows the EMA methodology. Among these, only those corresponding to blocks P3 (with 8 questions related to positive and negative affects) and P5 (with 21 questions related to emotion regulation strategies) have been considered. All questionnaires were answered with a value between 1 and 5, corresponding to the individual's level of agreement with the question asked. There were 36 attributes (predictors) that were used to train a model able to predict the level of depressive symptoms of the subject (between 1 and 5).

Before proceeding with the training, we performed a correlation analysis among the answers to the questionary. It is known that highly correlated variables provide very similar information to the model and, because of this, they can cause the model to overestimate the importance of that information, making the model unable to generalise well to new data. There is no clear correlation between attributes and, as a consequence, none of them were removed for this reason.

After correlation analysis, we also performed an attribute (feature) analysis and selection (Butcher & Smith, 2020). This analysis has been done using a Random Forest approximation and ordering the influence of each attribute on the result of the prediction. The goal of this analysis is to study if the ML models improve by sequentially removing (orderly) the less important attributes. This process is based on the hypothesis that the less important attributes tend to introduce noise into the model. Therefore, it is expected that by removing these attributes its performance increases.

2.6. Model Training

To obtain the best model able to predict the depressive symptoms level of a participant based on her social information and the mentioned questionary answers, we have proceeded in two sequential steps. The First Step was to find the best model using all the attributes gathered from each participant. In this way, the set of input samples was divided into training (with 70% of samples) and test (with 30% of samples). Both sets were generated in a stratified way to ensure that the number of samples of each type was equally proportional in both sets. During this first step, we also carried out the hyperparameter adjustment using the training set. This hyperparameter adjustment was performed by grid search using 5-fold cross-validation. The best combination of hyperparameters of each model was tested using the test set. Therefore, only the test set was used to check the correctness of the trained model using the best hyperparameters obtained after the hyperparameter search ensuring that the test samples were never seen by the model during the training process. The models that have been studied include: Linear Regression (LR), K-Nearest Neighbours (KNNr), Support Vector Machine (SVR), Neural Network (NN), Regression Tree (RT), and two ensemble models: Random Forest (RF) (Breiman, 2001) and XGBoost (XGB) (Chen & Guestrin, 2016). In this first step, we have also included a dummy model (Dummy) that always predicts the majority class. This will allow us to analyse how well the models are doing the predictions compared to a model that has not learned anything at all. Two metrics have been used to measure model fit: R-squared or R2 (Score) and mean-squared error (mse) (Chicco et al., 2021). R^2 indicates how much of the variability in the dependent variable can be accounted for by the independent variables included in the model. It ranges from 0 to 1, where a value of 0 indicates that the model does not explain any of the variability in the dependent variable, and a value of 1 indicates that the model explains this variability. However, a high R^2 does not necessarily mean that the model is accurate enough or that it is the best model for the data. This is why we have also considered the mean-square error (RMSE) to evaluate the accuracy of the models.

From the measures of model fit obtained by the test set, we construct an ordered list of models and choose the best one to perform the attribute selection described in the previous section. In the Second Step, the predictive attributes that gave the best results in the best model obtained in the First Step were used to “re-train” the predictive models with the hyperparameters obtained in step one.

3. Results

In the first step the search for hyperparameters and the best model was carried out and in the second step the selection of attributes and the "re-training" of the model was performed.

3.1. First Step: Hyperparameter search and search for the best model

As has been mentioned, the first step in the process of looking for the best model with the best hyperparameters (see Methods section) was performed using the 36 predictive attributes. In this way, the best hyperparameters obtained by a grid search were:

- LR: In Linear Regression, we have not searched the best hyperparameters, using the ones defined by default.
- KNNr: Number of neighbors set to 2.
- SVR: Radial basis function kernel.
- NN: Three hidden layers (of 150, 100, and 50 nodes), a learning rate of 0.01, and the “adam” solver.
- RT: Max depth 25 and minimum number of samples per leaf of 4.
- RF: Number of estimators 100 and minimum samples per leaf of 1.

- XGB: Learning rate of 0.4, max depth of 3, and the number of estimators set to 100.

Table 1 shows the measures of the metrics (see section Materials and Methods) in training and test for all the models trained with the best hyperparameters obtained by the grid search. As can be seen, the best models are NN and RF being a little bit better RF in test. Therefore, RF was the one used in Second Step for the attribute selection process. Finally, the last column of Table 1 shows the mean square error measure of the dummy model. As can be seen, even the LR model (the simplest one) improves this measure indicating that all models are able to learn with measures of fit well above the dummy model.

-- Insert Table 1--

3.2. Second Step: Attribute selection and model "re-training"

Having in mind that RF was the best model obtained in the previous step, this was the one used to analyse the effect of sequentially removing the less important attributes from the set of predictive ones. Figure 2 shows the effect of progressively removing the less important attributes. As can be seen, the performance of the RF model slightly improves until removing the less important 23 attributes, beginning to decline sharply thereafter. It should be noticed that only the set of training samples was used for this analysis.

-- Insert Figure 2--

After the attribute selection, the 13 attribute predictors remaining were: Age, Gender, Level of Studies, Job, Physical illness, Mental Distress, the following items related to affect: Enthusiastic (P3_4), Scared (P3_5), Satisfied (P3_6), and finally, in relation to the emotion regulation strategies ´I've tried not to pay attention to my emotions´(P5_9), ´I've sent messages or used social media to communicate how I felt´ (P5_14), I've diverted attention from my emotions´ (P5_16) and ´ I've tried to accept my emotions´ (P5_19).

Based on the results of the attribute selection, the models were re-trained using the best hyperparameters obtained in the First Step. Table 2 shows the results of this re-training. As can be seen, all models (except LR) significantly improve the results, obtaining R^2 closer to 1 and decreasing mean square error significantly. In this case, NN and RF are the best models again, being RF better in test.

-- Insert Table 2--

There is a significant contrast between the linear model (LR) and the remaining models assessed. Table 2 illustrates that the linear regression model (LR) values are considerably inferior to those of the other models. Observably, the R2 (training and test scores) is almost zero, and the MSE is relatively high. This suggests that the model performs slightly better than if the prediction returned the actual values' mean, resulting in a substandard approximation (Chicco et al., 2021). This indicates that the connection between the predictor attributes and the predictions is evidently non-linear, a characteristic successfully learned by all alternative non-linear models.

Finally, we built a confusion matrix to analyse how far the predictions are from the real values in the test set. This confusion matrix was built using the Random Forest model (the best one) trained after the attribute selection. As Figure 3 shows, of the 370, 336 are well classified while 32 have a deviation of only one level of depressive symptoms. However, there are two predictions that are a little far from the real values: one real depressive symptoms level 1 predicted as level 3 and one real depressive symptoms level 5 predicted as 2.

-- Insert Figure 3--

RF is an ensemble model based on bagging with which excellent results are usually obtained, but it turns out to be a black box model. These models lack transparency and make it difficult to understand why a particular prediction or decision was made. However, we were interested in knowing how each of the attributes selected in Step 2 affects the prediction. This last analysis has been made through Partial Dependence Plots (Molnar, 2022) or PDP. The PDPs are a way to visualize the relationship between a target variable and one or more predictor variables in a ML model. Specifically, a PDP shows the average relationship between a predictor variable and the target variable, while controlling for the effects of other predictor variables. In this way, we can obtain valuable insights into the behavior of ML models and help to improve our understanding of the relationships between predictor variables and target variables. As Figure 4 shows, some attributes (age, 'Enthusiastic' (P3_4), 'Scared' (P3_5), 'I've tried not to pay attention to my emotions' (P5_9), 'I've sent messages or used social media to communicate how I felt' (P5_14), 'I've diverted attention from my emotions' (P5_16)) positively influence (increase) the level of depressive symptoms. Among them, the ones that seem to have the greatest influence on increasing the level of depressive symptoms are 'Scared' (P3_5), 'I've sent messages or used social media to communicate how I felt' (P5_14), and age. The latter attribute shows a strange behavior at the extremes (at points 18 and 29) which could correspond to anomalous data and to the fact that there are few samples at these ages.

However, there are other attributes (gender, level of studies, physical illness, mental disorder, ´Satisfied´ (P3_6), ´I've tried to accept my emotions´ (P5_19) that negatively influence (decrease) the level of depressive symptoms. In this case, the attributes "level of studies" and ´Satisfied´ (P3_6) have the most influence on decreasing the predicted level of depressive symptoms. Of these, what is most striking is that, according to the model, having a physical or mental illness can decrease the level of depressive symptoms. However, it should also be noticed that the influence is so small that it may be the interaction with other factors that actually determine the final level of depressive symptoms.

-- Insert Figure 4--

4. Discussion

The aim of this study was to predict the level of depressive symptoms in emerging adults by analyzing sociodemographic variables, affect, and emotion regulation strategies. For this purpose, data collection was carried out through ecological momentary assessment and the data were analysed with machine learning techniques

Hypothesis 1 stated that positive and negative affect would be predictors of negative and positive symptoms of depression, respectively. The results are consistent with the hypothesis and with previous studies showing a relationship between affect and depressive symptoms (Cooke et al., 2022). Specifically, fear is one of the strongest predictors of high depressive symptoms. During emerging adulthood there is an increase in responsibilities and the person feels unstable and in search of his or her own identity (Arnett, 2014). The fear of facing new challenges, when it occurs on a daily and continuous basis, could be a relevant factor in the emergence of depressive symptoms. If adaptation to numerous changes is not adequate, it can lead to potentially harmful situations (Osma et al., 2021). Furthermore, the results showed that feeling satisfied is one of the most relevant predictors of low levels of depressive symptoms. These findings suggest that feeling satisfied with the way one's life is going may protect mental health during emerging adulthood.

Hypothesis 2 stated that the use of the emotion regulation strategies of rumination, suppression and distraction will be associated with higher levels of depressive symptoms; whereas the use of problem-solving, positive reappraisal, acceptance and social sharing strategies will be associated with lower levels of depressive symptoms. The results obtained are partially in line with the hypothesis, given that some of the emotion regulation strategies are significant predictors of depressive symptoms, but others do not seem to be determinant.

Daily use of distraction and social sharing strategies were associated with higher levels of depressive symptoms. With regard to distraction, distraction was found to be associated with more depressive symptoms. It is noted that directing attention to things other than emotions does not appear to be an effective strategy for emotional management in daily life and may be detrimental to mental health in emerging adulthood. Our results are congruent with previous studies (Nolen-Hoeksema et al., 2008) and contribute to elucidating the functioning of distraction, suggesting that its daily use may lead to maladaptive avoidance. Regarding social networking, the results are not in line with the hypothesised findings and show that texting or using social networks to share one's feelings may not be an effective regulation strategy in relation to depressive symptoms. One possible explanation could be related to emotional intelligence. According to Bucich & MacCann (2019), people with adequate emotional intelligence may benefit from sharing their emotions with others and positive relationships with other people are enhanced. It is possible that in the present study the participants did not have optimal emotional intelligence, which could mean that they did not benefit from the use of this strategy and that, on the contrary, an increase in depressive symptomatology was observed. Another possible explanation is related to the valence of the emotion being shared. Sharing emotions has been shown to amplify the emotional tone of triggering events, increasing the positive affect generated by a positive event, but also the negative affect generated by a negative event (Choi & Toma, 2014). The present research results reveal that fear and sharing emotions are the most relevant variables associated with an escalation in depressive symptoms. A possible explanation is that, during emerging adulthood, individuals may perceive the fear associated with facing the complexities of this developmental stage as an undesirable or negative emotion. When this emotion is shared with others, it not only fails to dissipate but instead intensifies, contributing to a heightened negative affect in the individual, potentially fostering the onset of depressive symptoms. It is possible that individuals who reported using social media or messaging to express their emotions in our research tended to express more negative affect than positive affect. Therefore, this regulation strategy seems to be associated with an increase in depressive symptoms. Likewise, acceptance was related to lower levels of depressive symptoms. These results are in line with previous studies that have shown the importance of acceptance of emotions in the treatment of mental disorders (Hofmann & Asmundson, 2008).

Problem solving strategies, rumination, positive reappraisal and emotional suppression were not predictors of depressive symptoms levels using ML. These results would not be in line with the hypothesis, however, they could be explained by contextual demands (Blanke et al., 2020; Boemo et al., 2022). It is possible that the functioning of emotion regulation strategies on a day-to-day basis is different from what has been observed when assessed cross-sectionally and retrospectively (Aldo et al., 2010). Further studies analysing the relationship between emotion regulation strategies and depressive symptoms using intensive longitudinal methods are needed given their importance in people's health (Brose et al., 2020; Lee & Choi, 2023).

Finally, hypothesis 3 stated that age and gender will predict the level of depressive symptoms, with women and older people having the highest levels. The results are in line with previous studies (WHO, 2023) and show that women are at higher risk of presenting symptoms of depression, as are older people. Therefore, it is necessary to pay special attention to women's mental health during emerging adulthood and to provide them with tools that enable them to cope with depressive symptoms in an effective way.

In terms of the advantages and limitations of the study, the use of EMA is a method that is being used to study behavior and mood in the settings in which they naturally occur (Courvoisier et al., 2010), and retrospective memory and report biases are greatly reduced (Wrzus & Neubauer (2022)). However, one of the drawbacks of EMA is that it requires a high number of users to complete the follow-up surveys must be high (Rintala et al., 2018; Wrzus & Neubauer, 2022). In our study, we expected that participants to complete at least, 65% of the surveys. To achieve this goal, and following the recommendations of Wrzus & Neubauer (2022), participants were offered financial compensation based on the number of surveys completed, with a minimum threshold of 65%. In addition, to keep the participants engaged, they could check the compliance rate and the number of surveys they had completed, but they could not see the results or access previous completed or incompleted surveys. An EMA study on mood, computer interruptibility and use found that providing participants with visualizations of their data resulted in a 23% higher compliance rate (Hsieh et al., 2008). Only the presentation of response rates has been shown to increase protocol compliance (Christensen et al., 2003). We believe that the combination of assessment days, assessments per day, ability to check response rates and incentives may have influenced the high compliance rate achieved in the present study.

The limited sample size of the present study restricts the generalizability of the results. To improve the generalizability of the findings, future investigations should consider a broader participant sample.

Liao et al. (2016) suggest that more standardized EMA reporting is needed and that studies need to be more rigorous and thorough in descriptions of methodology and results. To improve the reliability, efficacy, and overall interpretation of the findings for studies that use EMA, they developed a reporting checklist, which we considered when reporting this study. Therefore, the rigorousness of reporting the methodology of the study can also be considered a strength. However, future research should consider the feasibility and validation aspects that were lacking in the present study.

Finally, it should be noted that some randomized controlled trials have shown a positive effect of EMA on the detection of depressive symptoms (Kramer et al., 2014; McDevitt-Murphy et al., 2018). Nevertheless, two other studies did not find that kind of evidence (Bastiaansen et al., 2020; van Roekel et al., 2017), which is why Jimenez et al. (2022) consider that the effectiveness of EMA in reducing depressive symptoms should be further investigated. In this sense, we believe that the study presented in this paper can help to support the idea that EMA can indeed be an important tool in the early detection of depressive symptoms. However, the present study only included a healthy population of emerging adults who self-reported their depressive symptoms. Individuals with a diagnosed depressive disorder were not included in the study. Future research should consider the inclusion of individuals with a diagnosis of depression to identify day-to-day variables that may help to make an accurate diagnosis.

5. Conclusions

Depression is one of the most common mental illnesses in Spain, and indeed the world. Its early detection can help to control it without all the deterioration associated with the disease. In this sense, it is essential to effectively manage mental health on a daily basis (Tateyama et al., 2022) and the use of ML can be of great help (Yang et al., 2022). In this study, we have presented a tool capable of predicting the level of depressive symptoms using EMA as a continuous monitoring tool and ML algorithms to perform the predictions. Indeed, we regard as a strength of the current study the utilization of Ecological Momentary Assessment (EMA) and machine learning (ML) techniques to construct a valuable model for predicting depressive symptoms in emerging adults. This involved the incorporation of sociodemographic, affective, and emotion regulation variables, which had been employed individually in prior studies

In this way, we were able to use EMA to monitor patients on a daily basis and use the automatic learning models to identify the socio-demographic factors, affect and emotion regulation variables that were most influentian in predicting depressive symptoms. In fact, we have shown that the model is able to predict the level of depressive symptoms with an accuracy of over 98% in training and 92% in testing, using only the most important variables.

To overcome the limitations of our study, future research could include refining and validating the predictive model with larger samples, exploring long-term monitoring and intervention options, integrating the tool into digital health platforms, facilitating individualized treatment planning, implementing preventive measures and public health interventions, and addressing ethical considerations and privacy concerns. The development and application of such tools has the potential to improve early detection, personalized treatment, and overall mental health outcomes. We are also considering applying this study to other significant affective issues in our current society, such as symptoms of stress and anxiety.

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Table 1

Measures of the fit of the different models using R^2 and mean square error for training and test

Model	Score train	MSE train	Score test	MSE test	MSE dummy
LR	0.337300899	1.091418666	0.328638467	1.101268308	2.324324324
KNNr	1	0	0.739243091	0.427732757	2.324324324
SVR	0.856398441	0.236501636	0.807875057	0.315152269	2.324324324
Reg. Tree	0.917193522	0.136376428	0.792313173	0.340679215	2.324324324
NN	0.999784397	0.003030678	0.888227384	0.192225366	2.324324324
Random Forest	0.977577994	0.036927462	0.899403346	0.165013784	2.324324324
XGB	0.970008764	0.04939345	0.880072073	0.196723849	2.324324324

Note. Score train= R^2. MSE= mean square error.

Table 2

Measures of the fit of the different models using R^2 and mean square error for training and test after the attribute selection

Model	Score train	MSE train	Score test	MSE test
LR	0.269984164	1.20228458	0.251846591	1.227233908
KNNr	0.999648209	0.000579374	0.87376642	0.207067332
SVR	0.849500658	0.247861799	0.854466054	0.238726699
Reg. Tree	0.894578413	0.173621917	0.790124291	0.344269749
Random Forest	0.98240498	0.028977756	0.927903246	0.118263955
NN	0.991222305	0.014456244	0.916242314	0.137391972
XGB	0.952365215	0.078451131	0.908133252	0.150693676

Note. Score train= R^2. MSE= mean square error.

Figure 1

Flowchart of participants

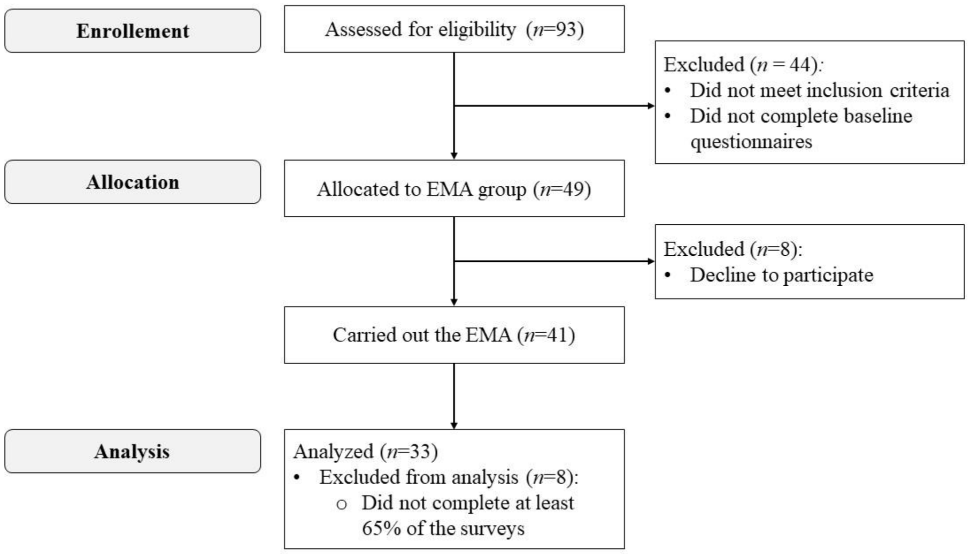

Figure 2

Effect of attribute selection on the best model obtained in the First Step.

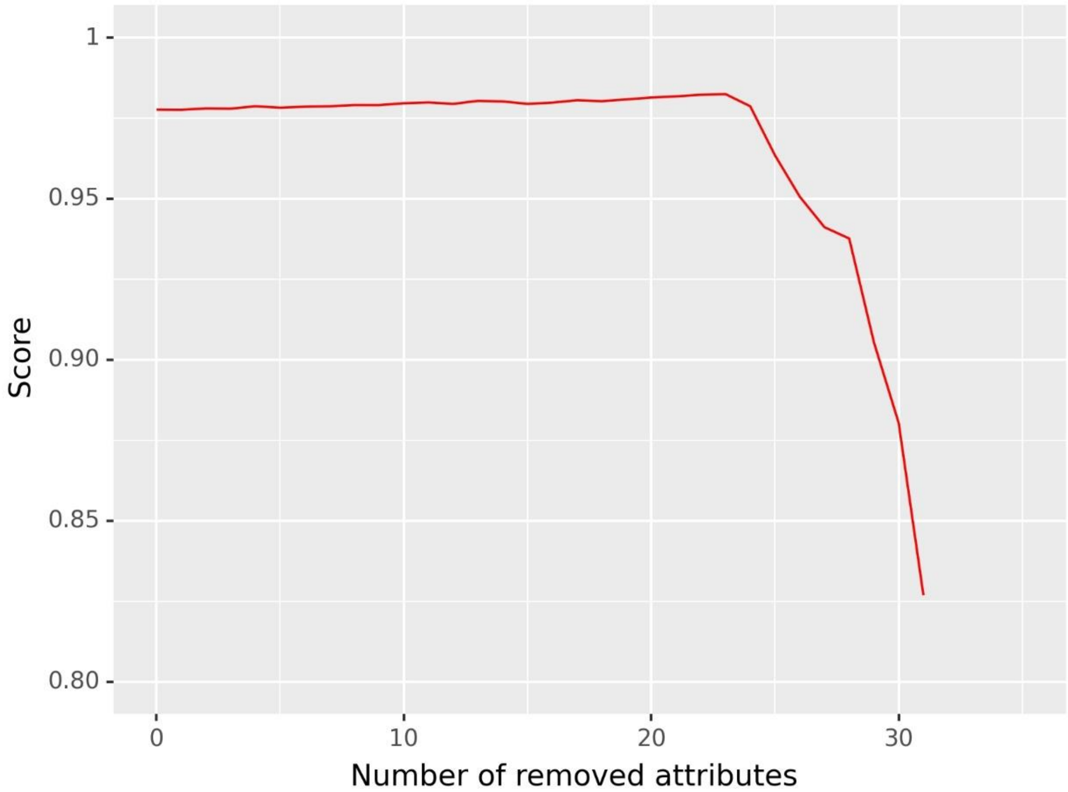

Figure 3

Confusion matrix.

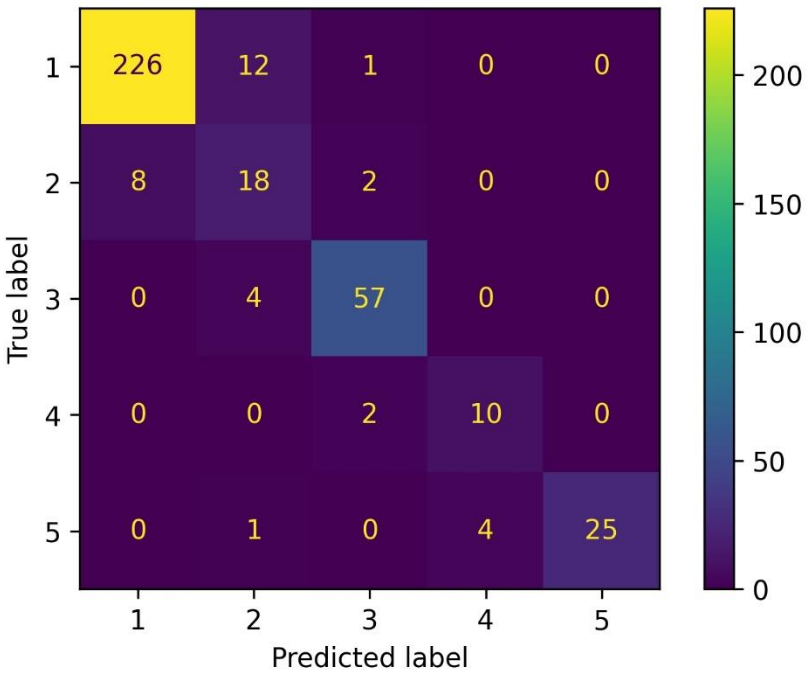

Figure 4

PDP analysis of the selected attributes.