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Research paper

A case for the use of deep learning algorithms for individual and population level assessments of mental health disorders: Predicting depression among China's elderly

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ABSTRACT

Background: With the continuous advancement of age in China, attention should be paid to the mental well-being of the elderly population. The present study uses a novel machine learning (ML) method on a large representative elderly database in China as a sample to predict the risk factors of depression in the elderly population from both holistic and individual level.

Methods: A total of participants met the inclusion criteria from the fourth waves of the China Health and Retirement Longitudinal Study (CHARLS) were analyzed with ML algorithms. The level of depression was assessed by the 10-item Center for Epidemiological Studies Depression Scale (CESD-10).

Results: The current study found top 5 factors that were important for predicting depression in the elderly population in China, including average sleep time, gender, age, social activities and nap time during the day. The results also provide reliable diagnostic likelihood at the individual level to support clinicians identify the most impactful factors contributing to patient depression. Our findings also suggested that activities such as interacting with friends and play ma-Jong, chess or join community clubs may have a positive collaborative effect for elderly's mental health.

Conclusions: Holistic approaches are an effective method of deriving and interpreting sophisticated models of mental health in elderly populations. More detailed information about a patient's demographics, medical history, sleeping patterns and social/leisure activities can help to inform policy and treatment interventions on a population and individual level. Large scale surveys such as CHARLS are effective methods for testing the most accurate models, however, further research using professional clinical input could further advance the field.

1. Introduction

Currently the world population increases to lean towards older average age, a trend that is expected to only increase as the number of elderly people over the age of 65 predicted to reach 16 % by 2050, and out-pacing both age groups 0–14 and 15–24 by 2075 (United Nations, 2022).

With the continuous advancement of age, greater support is required to maintain active lifestyle, good quality of life as well as mental well-being (Huang et al., 2022; Van Lente et al., 2012). With ever increasing number of elderly people several countries are experiencing challenges providing their elderly with the support and resources to do this. Large sections of a developed nations budget is dedicated to the physical needs of elderly people (Rudnicka et al., 2020), resulting in less availability for their mental well-being. One of the most prominent mental health disorders in both younger and older populations is depression (Major Depressive Disorder), characterized by a profound loss of pleasure, often accompanied by physical and cognitive changes, significantly affecting an individual's social or professional function (Uher et al., 2014). Depression is one of the three leading causes of Nonfatal Health Loss (James et al., 2018), and in recent years, the prevalence rate of depression has been rising, and the lifetime

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prevalence rate has reached 3.4 % (Huang et al., 2019). Depression is also one of the most common mental diseases among elderly population. The rate of depression among the elderly is between 5 % and 15 % in developed countries (Anderson, 2001) and >20 % in developing countries (Andrade et al., 2016).

Studies have shown that depressive symptoms are highly related to quality of life factors (Felce and Perry, 1995), that can be disproportionately impacted among older adults under certain circumstances (Cheraghi et al., 2019). Recent events such as the COVID-19 pandemic have gone on to exacerbate many of the areas of concern effecting the mental health of elderly individuals. Vectors of particular interest among researchers range from age related cognitive disorders like dementia (Borg et al., 2021; Gedde et al., 2022), to active lifestyle factors such as limited physical activity (Cvecka et al., 2015; Udeh-Momoh et al., 2021), social isolation (LeVasseur, 2021) and socio-economic factors related to marital status, income and leisure activities (Alexandre et al., 2009). Depression has a higher risk of recurrence, with a cumulative recurrence rate of 27.1 % within 20 years for individuals in remitted depression (Ten Have et al., 2018)., This is particularly damaging for older patients. Although depression has been shown to be treatable, the proportion of elderly people who seek help from medical institutions and receive timely treatment is often very low (Unützer et al., 2002).·Early identification of the elderly as population with a high risk of depression and a comprehensive description of the relevant risk factors is the key to early intervention to prevent depression in the elderly population.

The current research identifies three main aspects, as follows: (a) demographics and bio-information, such as gender (Potter and Yoon, 2023), age (Niu et al., 2023) and sleep (Nielson et al., 2023); (b) social activities, including internet use (Goh et al., 2023), physical activity (Glaus et al., 2023), leisure activities (Pan et al., 2023); (c) chronic disease risk factors, such as heart disease (Krittanawong et al., 2023), diabetes mellitus (Bao et al., 2023), cancer (Liu and Jia, 2023), cognitive function (Cullen et al., 2023).

Although most of these studies analyse the relationship between depression risk factors, there are some notable limitations to these studies when applying across age. Much of the prior research focuses on the relationship with biological indicators as risk factors, examining the genetic, neuroimaging testing comorbidity with other chronic diseases, and insomnia (Buch and Liston, 2021; Riemann et al., 2020). However, biological indicators can be difficult to interpret as they are also often used as diagnostic criteria, presenting a cyclical argument of causality (Gao et al., 2018; Jiang et al., 2016; Song et al., 2018; Xiao et al., 2018). Secondly, there were also studies investigated depression related risk factors based on cross-sectional data using traditional method such as logistic models; while these are the most prevalent method for their predictive efficacy they are limited by need for linear relationships, and are less effective for examining the more monotonic relationships expected in aging samples. With advancements in machine learning and generalized models it is possible to examine a multi-factor influence on a more individual basis moving away from the over-generalized methods previously used.

An often debated issue demonstrated with the previous research is the lack of predictive value at the individual level (Dunn et al., 2003). Regression and logistical modelling may work well on population bases, but are impractical and not particularly cost effective for diagnosing and correcting the issues suffered by elderly people (Dunn et al., 2003).

Compared with traditional prediction models, machine learning procedures have demonstrated excellent efficacy identifying nonlinear interactions between variables, being capable of aiding the analysis and interpretation across complex variables, particularly in multi-factorial situations where it is able to identify the most impactful variables and produce more robust predictive models (Iyortsuun et al., 2023). The utilisation of machine learning (ML) and deep learning techniques enables the iterative analysis of nonlinear, high-dimensional correlations among risk factors while simultaneously capturing temporal relationships between them (Lee et al., 2018; Orrù et al., 2012; Zhang et al., 2019). While a relatively new approach to data processing and analysis it is clear that researchers are slowly turning to machine learning as it provides greater accuracy in predictive modelling, especially when techniques are compared with each other and more traditional frequentist statistics (Sau and Bhakta, 2017). Several machine learning techniques have been adopted and tested over to past decade demonstrating a great deal of potential when combined with large datasets (Abd Rahman et al., 2020). The application of deep learning methods is of particular interest due to their ability to address many of the issues faced by clinicians and patients during the diagnosis and treatment selection process (Benrimoh et al., 2018).

Although the current literature appears promising, there are still several unanswered questions about the application of machine learning techniques, in addition to its inherently complex nature, which is preventing it from being applied more widely (Abd Rahman et al., 2020). The present study aimed to present how machine learning techniques can provide detailed information about the contributing factors to depression on a sample/population level as well as specific details at an individual level. The aims being to demonstrate the impact of this technology for researchers, policy makers as well as clinicians and patients. The algorithm will be trained on a large sample of the Chinese population based on the large and nationwide aging population database in China. This database, CHARLS (wave 4) has collected comprehensive information from >19,000 participants, including cognition and depression scale, such as the 10-item Center for Epidemiological Studies Depression Scale (CES-D-10), life satisfaction and other general measures including demographic backgrounds, health status and functioning.

The present study uses a large representative elderly database in China as a sample to investigate the following: 1) the use of the ML model to predict the risk factors of depression in the elderly population; 2) identify the most impactful of these risk factors for the purposes of targeted and efficient policy, and 3) demonstrate the potential diagnostic capacity of ML models to identify the risk of depression for elderly individuals and what are the most impactful factors for those individuals.

2. Method

2.1. Participants

All the data was collected using the fourth wave of the China Health and Retirement Longitudinal Study (CHARLS) collected in 2018. CHARLS is an ongoing longitudinal survey that aims to collect representative data from the Chinese population of people aged 45 and older for use in scientific research. The fourth wave was administered to 19,816 participants from 450 villages in 28 provinces, 150 counties/districts across China since 2011 (Zhao et al., 2020). CHARLS Data were collected through face-to-face interviews by trained investigators, and is considered to be one of the most comprehensive and well validated survey of its type, having been featured in several internationally recognised papers (Jiang et al., 2020; Wang et al., 2024; Yang and Hou, 2024). The complete data have been publicly released on the CHARLS website by the Institute of Social Science Survey at Peking University (Zhao et al., 2020).

From the survey dataset of 19,816 participants, a sample of 1558 was retained based on those who completed the questionnaires related to the core features of this study and were 60 years or older. Of these a further 289 were removed due to ambiguous answers such to core questions such as “I don’t know” or “refuse to answer”. This study selected a subsample of 1269 participants from the survey. Age was identified by asking for date of birth and subtracting from the date of the survey, for individuals who just provided their year of birth, a difference between it and the year of the survey was used. The average age of the sample was 67.54 with an age range of 60–94.

Of the final 1269 participants, 662 of the sample were male, and 607 were female. All participants were native born Chinese, with Mandarin Chinese being the most common first language and the language the survey was administered.

2.2. Measurement of depression/outcome variables

Part of the CHARLS measured the levels of depression using the Center for Epidemiological Studies Depression Scale-10 (CESD-10 scale), which is an effective screening instrument used by numerous studies researching depression among elderly populations (Irwin et al., 1999). The CESD-10 is a shortened version of the CESD-20 measure, and has been demonstrated to have good internal reliability (Cronbach's alpha = 0.86), and inter-rater reliability as compared to the CESD-20 (Kappa = 0.85) (Williams et al., 2020). The CESD-10 is most commonly used as a screening tool for depression in adult populations. It consists of 10 questions originally based on the diagnostic criteria for depression according to the DSM-III. Examples of the questions include "1. I was bothered by things that usually don't bother me." and "7. My sleep was restless.". The original CESD-10 items were measured on a scale of 0–3 with 0 representing "Rarely or none of the time (<1 day)", 1 representing "Some or a little of the time (1-2 days)", 2 representing "Occasionally or a moderate amount of the time (3-4 days)" and 3 representing "Most or all of the time (5-7 days)". The CHARLS version of the test also added an option for "Don't Know(DK)" and "Refuse to answer(RF)". The total score of the 10 questions ranged from 0 to 30, calculated by totalling all items scored after reverse scoring items 5 "I felt hopeful about the future." and 8 "I was happy.". Higher scores represented greater symptoms of depression, with a cut-off score of 10 representing the point at which the test is sensitive enough to identify clinical depression (Irwin et al., 1999). Four ordinal levels were analyzed based on clinical style cut-off points of <10 for no depressive symptoms, 10–14 for mild, 15–19 moderate, and > 20 for severe depressive symptoms (Andresen et al., 1994).

2.3. Predictors

The predictors used in this study can be split into 4 broad categories; (a) Demographic Backgrounds, such as gender and age; (b) Relationship with sleep , such as average hours of sleep at night, time spent asleep during the day (nap time). (c) Disease history, such as heart attack, dyslipidemia, chronic lung diseases, diabetes, kidney disease, stroke, liver disease, memory-related disease, and asthma; (d) Frequency of leisure and social behaviours associated with an active lifestyle, such as social activities with friends and family, playing board/table games, joining community clubs, and Internet use.

2.4. Data processing

Several regression based ML algorithms were conducted by AIforScience and produced by Beijing Diji Tech. All algorithms were regression based and included a Neural Network, AdaBoost, Elastic Net, Gradient Boosting Regression, Lasso Regression, Ridge Regression, and Random Forest Regression. They were trained using the CHARLS 2018 data set, with the aim of predicting severity of depressive symptoms based on a range of predictive factors. For each model the sample was split randomly into a training and test set with a 7:3 ratio. Each model was evaluated based on their R^2, the RMSE, SSE, and MAPE values.

The model with the best performance metrics were then examined further through model's feature importance and Shapley Additive Explanation (SHAP). SHAP is a powerful model interpretation package that enables examination of how the model achieved its conclusion by calculating the contribution of each predictor. It improves legibility and transparency while, crucially also being capable of providing information at the individual and feature level, enabling an understanding of the directionality of individual predictions. The higher SHAP value for a given prediction the more that predictor/feature contributed to the predicted outcome. Due to it's high computational cost limitations are typically present with the amount of data that can be evaluated at this level. In this case only the best preforming model was assessed.

3. Results

This study aimed to identify the contributing factors of depression among older adults. Regression based supervised machine learning algorithms were used to predict the level of depression, using demographic, medical and lifestyle information.

3.1. Descriptive statistics

The ordinal depression groups were heavily weighted towards the no depression ($N = 776$), the mild depression ($N = 222$), moderate depression ($N = 165$), and severe depression ($N = 106$) groups made up approximately a third of respondents ($Mdn = 0$, $IQR = 1/M = 0.69$, $SD = 0.99$).

Scores for the 27 predictors can be categorised into 4 broad categories, demographic information, relationship with sleep, medical history and social/leisure engagement. Means, standard deviations and percentage frequencies are provided as appropriate (Table 1).

Given the older demographic under investigation, engagement with many of these activities appeared rather low. In an effort to identify whether abstaining from any social or leisure activities were a predictor

Table 1
Means, standard deviations and sample proportions for the predictor variables.

Variable	Mean	Standard deviation
Demographic data		
Age (years)	67.54	6.18
Gender (percentage female)	47.83	49.97
Relationship with sleep		
Sleep per night (hours)	6.09	2.1
daytime napping (min)	41.36	48.69
Leisure and social activities[a]		
Interact with friends	58.71	105.06
Ma-jong, chess, cards, or community club	33.88	83.98
Provide help to family, friends, or neighbours	17.18	51.37
Sport, social, or other kind of club	13.48	59.17
Take part in a community-related organization	3.31	22.57
Voluntary or charity work	1.97	16.5
Care for a sick or disabled adult	5.44	34.54
Educational or training course	0.87	13.44
Stock investment	1.34	18.79
Use the internet	14.26	62.87
Other activities	2.05	20.92
Social activities (Y/N)	67.54	6.18

Variable	Percentage
Medical history[b]	
Dyslipidemia	8.83
Diabetes	5.44
Cancer	1.42
Chronic lung diseases	6.78
Liver disease	3.15
Heart attack	7.57
Stroke	4.26
Kidney disease	5.20
Emotional problems	0.63
Memory-related disease	1.65
Asthma	1.65

[a] Medical history section provides the prevalence of several common conditions within the sample as a percentage.

[b] Leisure and Social activities were recorded on a 4 point Likert scale measuring frequency of engagement, higher scores represent higher engagement with that activity. Original wording translated from the CHARLS Chinese user manual.

of depression an additional binary classification was considered labeled "Social Activities (Y/N)". If the participant did not engage in any of the 12 social and leisure activities then they received a score of 12, whereas if they took part in any of the activities they received a score of 0. Using this method 54 % of participants were found to not engage in any of the activities.

3.2. Model prediction performance

The diagnosis of a depressive disorder relies on a combination of standardised psychometric testing and discussions with a clinician. While the more detailed interviews are crucial for this process, clinicians still rely on a categorical approach when initially screening for depression to make the decision to investigate further. In the CHARLS dataset, the CESD-10 represents this as 4 potential levels ranging from no depression to mild and then moderate and severe.

Several supervised regression based models were trained on the CHARLS dataset in an attempt to identify patterns in risk factors that could contribute to contribute to scoring more highly on initial diagnostic tests. A summary of their performance is provided in Table 2. Of the models trained the neural network regression model was able to explain the most variability for the measure of depression according to the CESD-10 criteria ($R^2 = 0.69$), with the closest comparative score being that of the Random forest regression ($R^2 = 0.52$). The RMSE of 0.61 signifies that the average prediction error is 0.61 units on the depression scale, reflecting a reasonable level of precision. The SSE value of 138.06 represents the total squared deviation of the predicted values from the actual values, providing an aggregate measure of the model's error. Additionally, the MAPE of 0.14 indicates that the model's predictions are, on average, 14 % off from the actual values, demonstrating a satisfactory level of accuracy.

Overall, these results highlight that the neural network regression model performs competently in predicting depression scores, though there is still room for enhancement through further model refinement and optimization.

3.3. Feature importance

Due to scaling differences in the calculation of SHAP values they cannot be compared between different underlying models, as such further evaluation focused on the neural network model. One utilisation of SHAP values are at the general feature level, identifying the most impactful variables for the output. Fig. 1 shows the SHAP values for the combination of feature importance for all predictors based on the developed prediction model. The X-axis represents the SHAP value, and the Y-axis shows each variables with the most impactful at the top. The result indicated that average hours of sleep is the most important feature in predicting depressive symptoms. Secondary to the hours of sleep is gender. Age, activities, nap time and interaction with friends are also among the predictors with highest contributions in predicting depression among CHARLS participants.

3.4. Interpretation of model features

One of the most important feature of a prediction model is that it can

Table 2
Regression model performance metrics.

Model	R^2	RMSE	SSE	MAPE
Adaboost regression	0.35	0.81	510.82	0.48
Lasso regression	0.32	0.81	486.36	0.46
Ridge regression	0.42	0.79	376.03	0.42
ElasticNet linear regression	0.28	0.80	673.94	0.51
Gradient boosting regression	0.42	0.77	358.77	0.37
Random forest regression	0.52	0.73	292.51	0.26
Neural network	0.69	0.61	138.06	0.14

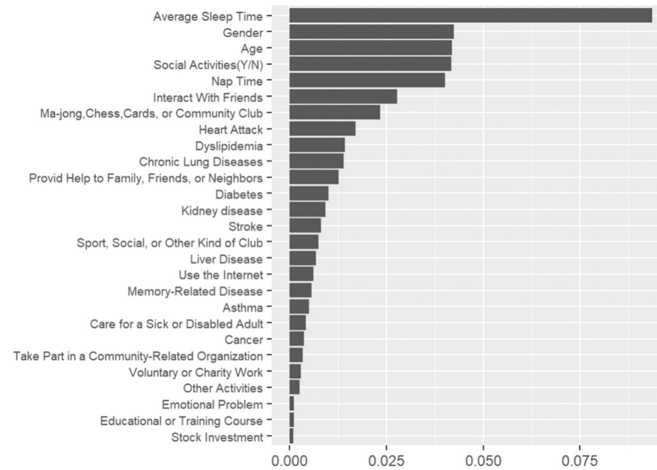

Fig. 1. The average SHAP value for feature contribution to the predictive model in descending order of feature importance.

be directly explained and interpreted, The SHAP approach computed each variable's contribution to the prediction. Fig. 2 shows how predictors effect the estimated risk of depression, and the top five important predictors based on the SHAP value calculation were selected and plotted out in order to facilitate understanding of how a single predictor affects the output of the prediction model. The Y-axis indicates the SHAP values calculated by the model, and the X-axis represents the data for that variable. Each dot represents an individual response and it's impact on the prediction outcome. The value 0 represents a cut off point for the SHAP value, positive values indicate a higher push to the prediction of depression. Fig. 2A showed gradual pattern of SHAP value decline indicating those who had more sleep (particularly 5.5 to 8.5 h), contributing less to a prediction of depression. Fig. 2B demonstrated that being female increased the likelihood of a prediction of depression. Fig. 2C depicted that individuals in their early 60s are more prone to have higher level of depression, and the trend gradually declined as they reaches 70, particularly there is limited evidence of the influence of age between 65 and 75. After 75 SHAP values have greater variability but generally trend downwards. Indicating a potential trend of lower depression at the further ends of the scale, but also that data becomes more sparse. Fig. 2D indicated that individuals who did not engage in social activities contributed to greater predictions of depression. Finally, Fig. 2E illustrated that those who sleep longer hours during the day were overall more likely to lead to greater predictions of depression, however the chart presents a widening variability in SHAP values with greater daytime sleep, suggesting that the influence of sleep during the day may interact with other variables. Each plot shows that while there are general trends, for some individuals the feature had no impact on depression, or even mitigated against it according to the model.

3.5. Force plots for individual predictions

One of the more interesting applications is the assessment of individuals using SHAP values. Fig. 3 shows the SHAP force plot for predicting depression among elderly population. The explainable machine learning model proposed in this study can perform customized analysis for individual participants. As shown in Fig. 3, the model can provide explanation of how each variable specifically affects the prediction at an individual level. The present study selected four cases as sample cases for customized analysis for individuals, including one case (Fig. 3A) of an individual with the greatest depression score on the (depression score = 3), one case of an individual (Fig. 3B) with no evidence of depression (depression score = 0), one case of an individual (Fig. 3C) among the oldest sampled (age = 94), and a random case (Fig. 3D). The output value (the bold number above the force plot) represents

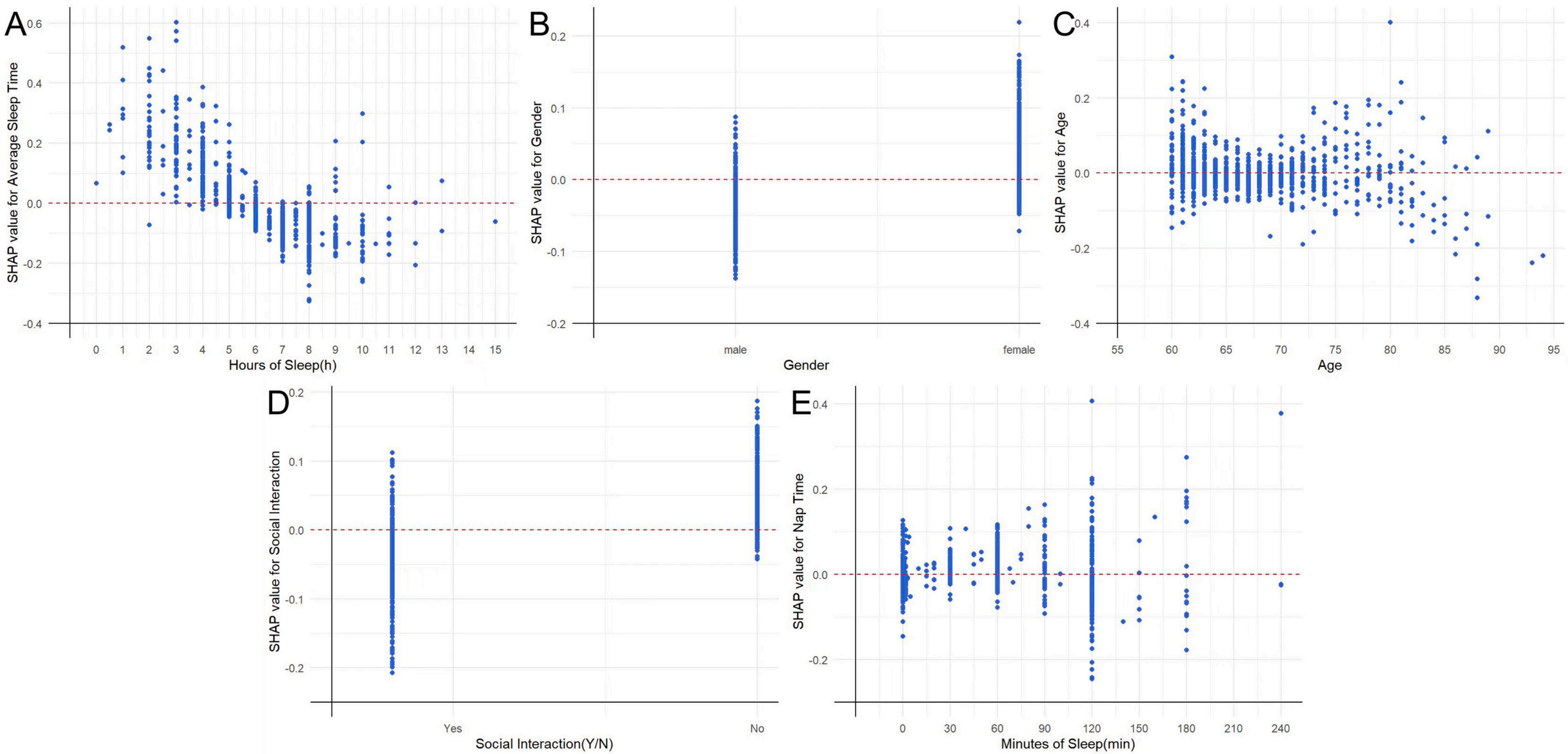

Fig. 2. SHAP value by features for the most impactful according to the mean feature importance.
Note: Higher SHAP value indicates greater contribution to the predicted outcome (scoring higher for depression according the CESD-10).

Fig. 3. Force plot representing the influence of specific feature on individual predictions.
Note: According to the Survey of CHARLS, gender (1 = male, 2 = female); activities (0 = Yes, and 12 = None); average sleep time (number of hours spent sleeping each night); nap time (number of minutes napping during the day); heart attack (1 = Yes, 2 = No); dyslipidemia (1 = Yes, 2 = No); ma-jong, chess, card, or community club (0 = None, 1 = Not Regularly, 2 = Almost Every Week, 3 = Almost Every Day); interact with friend (0 = None, 1 = Not Regularly, 2 = Almost Every Week, 3 = Almost Every Day).

predicted value of the depression scale for that individual. As SHAP values are all relative to certain base value, the base value (as indicated by the location of the grey text) represents the mean of the raw model predictions for the training data. The red features on the left of each force plot represents the variables contributing to an increase in the prediction of the depression score (drives ML prediction value up), while the blue features on the right represents the variables that reduce the prediction of depress (drives ML prediction value down). In clearer terms, red variables contribute to depression while blue variables mitigates against depression according to the model. Each set of features is ranked in order of their impact on the value, and the features with the greatest impact are labeled.

Fig. 3A describes the case that had the highest prediction of depression over the average prediction across the whole sample. Top features contributing to the prediction of depression were the lack of average sleep time (2.5 h), long periods of day-time sleeping (180 min of nap time), lack of social activities (no social or leisure activities reported) and their gender (female). Top mitigating features were their relatively young age (63) and lack of interaction with friends (no interaction). Fig. 3B represents a case that did not show evidence of depression according to the CESD-10, that the model correctly identified as not exhibiting signs of depression. Top mitigating features included the average sleep time (7 h), nap time (120 mins), social activities participation, age (63) and playing ma-jong, chess, cards or participating in a community club. Fig. 3C represents the oldest participant in the sample. Top mitigating features are Age (94) and Gender (male). Fig. 3D depicts case selected at random from the sample. Top features contributing to depression were lack of social activities. Top mitigating feature are average sleep time (6 h), gender (male), no heart attack and no regular day time sleeping.

4. Discussion

In this study, individual risk factors for developing depressive disorder in the elderly population were found to be predicted with reasonable accuracy by using well trained neural networks. Additionally, the developed model identified the top factors that were important for predicting depression in the elderly population from the comprehensive survey of predictors, including average night time sleep, gender, age, social activities and day time sleeping. The impactful features identified in this study are largely consistent with other machine learning studies, who typically utilise classification based models with high levels of accuracy and AUC metrics ranging between 0.67 and 0.96 (Hatton et al., 2019; Kim et al., 2019; Lin et al., 2023). These are typically higher than regression and other classical statistics based methods (Hatton et al., 2019), however more sophisticated regression based techniques may be able to offer more nuanced insights into complex disorders with multifactorial causes, symptomologies and requirement (Lu et al., 2021).

Comparing the results of the machine learning algorithm with the findings of previous research indicated convergence around the factor of sleep and it's strong associations with depression (Lyall et al., 2023; Simjanoski et al., 2022; Chuinsiri, 2021). This method argues that sleep is not only a symptom, but also a risk factor of depression. The results of the current study indicates that majority of individuals who sleeps 5.5 to 8.5 h per night have a lower risk of depression. Sleep is a very important factor affecting health, studies indicated that lack of sleep at night may contribute to the onset of mental disorders (Hong et al., 2019; Li et al., 2017; Gehrman et al., 2013; Luik et al., 2015). Sleep deficiency can disrupt the circadian rhythm or cause hormonal changes (Kim et al., 2015). Daytime physical fatigue or mental fatigue is also correlated with poor night sleep quality, resulting in higher risk of depression. The result of our studies showed that individuals with substantial time of nap during the day have a lower chance of suffering from depression.

The results of the model are largely consistent with previous research demonstrate across the majority of the tested predictors. In particular the model was able to support the widely discussed finding that female elderly population are general are more likely to suffer from later-life depression when compared to age matched males (Kiely et al., 2019). Several potential arguments have been presented for the higher rates of depression among elderly females. This includes physiological factors such as a drop in oestrogen levels due to menopause and physical discomfort (Lokuge et al., 2011); social factors, such as the stress of societal expectations not present for elderly males, such as being primarily responsible for maintaining the household while her husband has likely retired from his work. In addition to recorded psychological/personality trait differences between males and females making women more prone to feelings of depression (Bareeqa et al., 2021; Li et al., 2022). Interestingly, previous research has demonstrated that unmarried or women who widowed early into their 60 were less likely to display symptoms of depression (Bulloch et al., 2017). Indicating an interaction between the variables. While this was not examined directly in this study, individuals assessments using the force plots identified several features/predictors that had seemingly contradictory effects on the predictions of depression. A potential explanation for this could be the model identifying that specific combinations of features could lead to an increase or a mitigation of other risk factors. This is could be highly beneficial for clinicians who wish to have more nuanced diagnostic tool that can factor in multiple relevant aspects of an individual's circumstance to provide more accurate and effective treatment plans.

The current study found an interesting and novel curvilinear relationship between age and depression. The results indicated that elderly in their early 60 appear to be more depressed, but the symptoms start to attenuate and remain stable for individuals age 65 to 70. The level of depression starts to increase among elderly aged 75, and may decrease again after age 85. These trends may be the product of interaction between the assessed variables, as seen in the force plots where a younger age was seen as both a contributing and mitigating factor in different participants. Other extraneous variables are also likely to confound the impact of age in these circumstances. As the data for participants over 80 was more sparse the SHAP diagrams showed that there was greater variability in this older demographic. More finely tuned models with larger samples and broader feature sets may help to identify the multifactorial nature of this trend.

Previous studies suggested that social activities is one of the predictive factors for depression (Chiao et al., 2011; Wang et al., 2020). The result of the current study supported these findings that elderly individuals with more social activities present a lower risk of depression compared with those who report no social activities. Our findings also suggested that activities such as interact with friends and play ma-jong, chess or join community clubs are positive promoting effect for elderly's mental health.

A common limitation of machine learning approaches are the number of potential trade-offs when selecting variables, tuning and the use of different types of models (Stenwig et al., 2022). While different approaches were tested, refining the model through better data selection and model tuning could help provide more accurate models. Importantly in this study the SHAP values provide greater insight and transparency regarding the prediction process of the model. SHAP values enabled a more nuanced understanding of the influence of individual datapoints for each variable, beyond what can be communicated by performance metrics alone. Of particular note was that the SHAP value visualisations show clearly how some features could be a strong predictor of depression in one instance but offer little evidence in different circumstances. This is most strongly conveyed in the force plots for individual participants. With it clearly demonstrating the complicated relationship between features. The findings presented in this study demonstrate that using novel machine learning techniques can support a nuanced interpretation of large and complex assessments to examine trends and commonalities, presenting the findings in a more intuitive manner that may aid researchers when discussing potential risk factors at both a population level and an individual level. Supporting communication between researchers and policy makers, as it can demonstrate the most consistent factors to target, while also identifying the situation where intervention may have diminishing returns or limited efficacy.

On a more individual level it also provides a data-driven diagnostic likelihood that may support clinicians in identifying the most influential factors contributing to a patient's depression. It is important to clarify that the force plots presented still need to be interpreted with care, they are not prescriptive of any one individual, as they still rely on the averages across the entire dataset, attempting to highlight features that the model has determined to be important based on other individuals in similar circumstances. However, with larger and more detailed datasets, in combination with well optimised algorithms, this could provide more bespoke insights that may lead to precise treatment plans tailored at the individual level (Bohr and Memarzadeh, 2020). Currently the limited application of ML methods within health care limits their efficacy in real world settings. Apprehension around the use of such models is in part due to a lack of transparency and understanding of how ML model reach their predictions and how they can be interpreted safely (Amann et al., 2020).

While SHAP values offer a promising direction for improving interpretability of machine learning predictions, this study is similarly limited as a practical use case. To support accurate prediction large amounts of data are required, lending itself more to fields outside of manpower intensive field of psychology where participant numbers are unable to match the millions of data points seen in comparable computer science and bioscience studies. The use of national surveys such as the CHARLS provide the greatest access to larger samples, however this also comes with needing to rely on relatively shallow assessments of mental health. Here the measure of depression relies on CESD-10, the utilisation of a screening scale are not as accurate as the clinical diagnosis from a professional clinical psychologist or a psychiatrist (Zhou et al., 2021). Future research incorporating the experience of clinicians could help to train models to provide accurate diagnosis based on real life data. This could help find patterns more quickly and reduce the trial and error of treatment plans effecting most mental health disorders. Despite depression being one of the most prevalent psychological disorder impacting of the Chinese population, and costing approximately $42.67 per capita, it is often overlooked or misdiagnosed with a detection rate of 30.3 % (Nisar et al., 2020). A delay or lack of diagnosis of depression can have severe adverse effects leading to substantial depression in quality of life similar to that of other chronic medical conditions. Improvements in the efficiency and speed of diagnosis offered by machine learning can result in improvements to the life of a large section of the population and ease the financial burden placed on governments.

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CRediT authorship contribution statement

Yingjie Wang: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xuzhe Wang:** Software, Investigation, Formal analysis, Data curation. **Li Zhao:** Methodology, Investigation, Formal analysis, Data curation. **Kyle Jones:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yingjie Wang reports financial support, administrative support, article publishing charges, equipment, drugs, or supplies, travel, and writing assistance were provided by National Social Science Fund of China. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

All data that support the findings of this study are included in this manuscript and supplementary information files.

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References

Abd Rahman, R., Omar, K., Noah, S.A.M., Danuri, M.S.N.M., Al-Garadi, M.A., 2020. Application of machine learning methods in mental health detection: a systematic review. Ieee Access 8, 183952–183964.

Alexandre, T. da S., Cordeiro, R.C., Ramos, L.R., 2009. Factors associated to quality of life in active elderly. Revista De Saude Publica 43 (4), 613–621. https://doi.org/10.1590/s0034-89102009005000030.

Amann, J., Blasimme, A., Vayena, E., Frey, D., Madai, V.I., the Precise4Q consortium, 2020. Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. BMC Med. Inform. Decis. Mak. 20 (1), 310. https://doi.org/10.1186/s12911-020-01332-6.

Anderson, D.N., 2001. Treating depression in old age: the reasons to be positive. Age Ageing 30 (1), 13–17. https://doi.org/10.1093/ageing/30.1.13.

Andrade, F.C.D., Wu, F., Lebrão, M.L., Duarte, Y.A. de O., 2016. Life expectancy without depression increases among Brazilian older adults. Revista De Saude Publica 50, 12. https://doi.org/10.1590/S1518-8787.2016050005900.

Andresen, Elena M., et al., 1994. Screening for depression in well older adults: evaluation of. Prev. Med. 10, 77–84.

Bao, Y.K., Miller, C.J., Narayanan, S.S., Gaddis, M., Drees, B.M., 2023. Prevalence and risk factors of major depression in patients with diabetic retinopathy in a nationally representative survey. Ophthalmic Epidemiol. 30 (5), 462–467. https://doi.org/10.1080/09286586.2023.2172189.

Bareeqa, S.B., Ahmed, S.I., Samar, S.S., Yasin, W., Zehra, S., Monese, G.M., Gouthro, R. V., 2021. Prevalence of depression, anxiety and stress in china during COVID-19 pandemic: a systematic review with meta-analysis. Int. J. Psychiatry Med. 56 (4), 210–227. https://doi.org/10.1177/0091217420978005.

Benrimoh, D., Fratila, R., Israel, S., Perlman, K., Mirchi, N., Desai, S., Rosenfeld, A., Knappe, S., Behrmann, J., Rollins, C., You, R.P., Aifred Health Team, T, 2018. Aifred health, a deep learning powered clinical decision support system for mental health. In: Escalera, S., Weimer, M. (Eds.), The NIPS '17 Competition: Building Intelligent Systems. Springer International Publishing, pp. 251–287. https://doi.org/10.1007/978-3-319-94042-7_13.

Bohr, A., Memarzadeh, K., 2020. Chapter 2—the rise of artificial intelligence in healthcare applications. In: Bohr, A., Memarzadeh, K. (Eds.), Artificial Intelligence in Healthcare. Academic Press, pp. 25–60. https://doi.org/10.1016/B978-0-12-818438-7.00002-2.

Borg, C., Rouch, I., Pongan, E., Getenet, J.C., Bachelet, R., Herrmann, M., Bohec, A.-L., Laurent, B., COVCARE Group, Rey, R., Dorey, J.-M., 2021. Mental health of people with dementia during COVID-19 pandemic: what have we learned from the first wave? Journal of Alzheimer's Disease: JAD 82 (4), 1531–1541. https://doi.org/10.3233/JAD-210079.

Buch, A.M., Liston, C., 2021. Dissecting diagnostic heterogeneity in depression by integrating neuroimaging and genetics. Neuropsychopharmacology: Official Publication of the American College of. Neuropsychopharmacology 46 (1), 156–175. https://doi.org/10.1038/s41386-020-00789-3.

Bulloch, A.G.M., Williams, J.V.A., Lavorato, D.H., Patten, S.B., 2017. The depression and marital status relationship is modified by both age and gender. J. Affect. Disord. 223, 65–68. https://doi.org/10.1016/j.jad.2017.06.007.

Cheraghi, P., Eskandari, Z., Bozorgmehr, S., Zanjari, N., Cheraghi, Z., 2019. Quality of life and its related factors among elderly people. Journal of Education and Community Health 6 (3), 145–151.

Chiao, C., Weng, L.-J., Botticello, A.L., 2011. Social participation reduces depressive symptoms among older adults: an 18-year longitudinal analysis in Taiwan. BMC Public Health 11, 292. https://doi.org/10.1186/1471-2458-11-292.

Chuinsiri, N., 2021. Unsupervised machine learning identified distinct population clusters based on symptoms of oral pain, psychological distress, and sleep problems. Journal of International Society of Preventive & Community Dentistry 11 (5), 531–538. https://doi.org/10.4103/jispcd.JISPCD_131_21.

Cullen, B., Gameroff, M.J., Ward, J., Bailey, M.E.S., Lyall, D.M., Lyall, L.M., MacSweeney, N., Murphy, E., Sangha, N., Shen, X., Strawbridge, R.J., van Dijk, M.T., Zhu, X., Smith, D.J., Talati, A., Whalley, H.C., Cavanagh, J., Weissman, M.M., 2023. Cognitive function in people with familial risk of depression. JAMA Psychiatry 80 (6), 610–620. https://doi.org/10.1001/jamapsychiatry.2023.0716.

Cvecka, J., Tirpakova, V., Sedliak, M., Kern, H., Mayr, W., Hamar, D., 2015. Physical activity in elderly. European Journal of Translational Myology 25 (4), 249–252. https://doi.org/10.4081/ejtm.2015.5280.

Dunn, G., Mirandola, M., Amaddeo, F., Tansella, M., 2003. Describing, explaining or predicting mental health care costs: a guide to regression models. Methodological review. Br. J. Psychiatry J. Ment. Sci. 183, 398–404. https://doi.org/10.1192/bjp.183.5.398.

Felce, D., Perry, J., 1995. Quality of life: its definition and measurement. Res. Dev. Disabil. 16 (1), 51–74. https://doi.org/10.1016/0891-4222(94)00028-8.

Gao, S., Calhoun, V.D., Sui, J., 2018. Machine learning in major depression: from classification to treatment outcome prediction. CNS Neurosci. Ther. 24 (11), 1037–1052. https://doi.org/10.1111/cns.13048.

Gedde, M.H., Husebo, B.S., Vahia, I.V., Mannseth, J., Vislapuu, M., Naik, M., Berge, L.I., 2022. Impact of COVID-19 restrictions on behavioural and psychological symptoms in home-dwelling people with dementia: a prospective cohort study (PAN.DEM). BMJ Open 12 (1), e050628. https://doi.org/10.1136/bmjopen-2021-050628.

Gehrman, P., Seelig, A.D., Jacobson, I.G., Boyko, E.J., Hooper, T.I., Gackstetter, G.D., Ulmer, C.S., Smith, T.C., 2013. Predeployment sleep duration and insomnia symptoms as risk factors for new-onset mental health disorders following military deployment. Sleep 36 (7), 1009–1018. https://doi.org/10.5665/sleep.2798.

Glaus, J., Kang, S.J., Guo, W., Lamers, F., Strippoli, M.-P.F., Leroux, A., Dey, D., Plessen, K.J., Vaucher, J., Vollenweider, P., Zipunnikov, V., Merikangas, K.R., Preisig, M., 2023. Objectively assessed sleep and physical activity in depression subtypes and its mediating role in their association with cardiovascular risk factors. J. Psychiatr. Res. 163, 325–336. https://doi.org/10.1016/j.jpsychires.2023.05.042.

Goh, Z.H., Tandoc, E.C., Chan, V.X., 2023. Alone and lonely? How physical and perceived isolation can lead to problematic internet use. Behav. Inform. Technol. 42 (15), 2588–2600. https://doi.org/10.1080/0144929X.2022.2134825.

Hatton, C.M., Paton, L.W., McMillan, D., Cussens, J., Gilbody, S., Tiffin, P.A., 2019. Predicting persistent depressive symptoms in older adults: a machine learning approach to personalised mental healthcare. J. Affect. Disord. 246, 857–860. https://doi.org/10.1016/j.jad.2018.12.095.

Hong, J., Aspey, L., Bao, G., Haynes, T., Lim, S.S., Drenkard, C., 2019. Chronic cutaneous lupus erythematosus: depression burden and associated factors. Am. J. Clin. Dermatol. 20 (3), 465–475. https://doi.org/10.1007/s40257-019-00429-7.

Huang, Y., Wang, Y., Wang, H., Liu, Z., Yu, X., Yan, J., Yu, Y., Kou, C., Xu, X., Lu, J., Wang, Z., He, S., Xu, Y., He, Y., Li, T., Guo, W., Tian, H., Xu, G., Xu, X., Wu, Y., 2019. Prevalence of mental disorders in China: a cross-sectional epidemiological study. Lancet Psychiatry 6 (3), 211–224. https://doi.org/10.1016/S2215-0366(18)30511-X.

Huang, L., Li, X., Gu, X., Zhang, H., Ren, L., Guo, L., Liu, M., Wang, Y., Cui, D., Wang, Y., Zhang, X., Shang, L., Zhong, J., Wang, X., Wang, J., Cao, B., 2022. Health outcomes in people 2 years after surviving hospitalisation with COVID-19: a longitudinal cohort study. Lancet Respir. Med. 10 (9), 863–876. https://doi.org/10.1016/S2213-2600(22)00126-6.

Irwin, M., Artin, K.H., Oxman, M.N., 1999. Screening for depression in the older adult: criterion validity of the 10-item Center for Epidemiological Studies Depression Scale (CES-D). Arch. Intern. Med. 159 (15), 1701–1704. https://doi.org/10.1001/archinte.159.15.1701.

Iyortsuun, N.K., Kim, S.-H., Jhon, M., Yang, H.-J., Pant, S., 2023. A review of machine learning and deep learning approaches on mental health diagnosis. Healthcare (Basel, Switzerland) 11 (3), 285. https://doi.org/10.3390/healthcare11030285.

James, S.L., Abate, D., Abate, K.H., Abay, S.M., Abbafati, C., Abbasi, N., Abbastabar, H., Abd-Allah, F., Abdela, J., Abdelalim, A., Abdollahpour, I., Abdulkader, R.S., Abebe, Z., Abera, S.F., Abil, O.Z., Abraha, H.N., Abu-Raddad, L.J., Abu-Rmeileh, N. M.E., Accrombessi, M.M.K., et al., 2018. Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 392 (10159), 1789–1858. https://doi.org/10.1016/S0140-6736(18)32279-7.

Jiang, H., Popov, T., Jylänki, P., Bi, K., Yao, Z., Lu, Q., Jensen, O., van Gerven, M., a. J., 2016. Predictability of depression severity based on posterior alpha oscillations. Clin. Neurophysiol. 127 (4), 2108–2114. https://doi.org/10.1016/j.clinph.2015.12.018.

Jiang, C.-H., Zhu, F., Qin, T.-T., 2020. Relationships between chronic diseases and depression among middle-aged and elderly people in China: a prospective study from CHARLS. Current Medical Science 40 (5), 858–870. https://doi.org/10.1007/s11596-020-2270-5.

Kiely, K.M., Brady, B., Byles, J., 2019. Gender, mental health and ageing. Maturitas 129, 76–84. https://doi.org/10.1016/j.maturitas.2019.09.004.

Kim, T.W., Jeong, J.-H., Hong, S.-C., 2015. The impact of sleep and circadian disturbance on hormones and metabolism. Int. J. Endocrinol. 2015, e591729. https://doi.org/10.1155/2015/591729.

Kim, H., Lee, S., Lee, S., Hong, S., Kang, H., Kim, N., 2019. Depression prediction by using ecological momentary assessment, Actiwatch data, and machine learning: observational study on older adults living alone. JMIR Mhealth Uhealth 7 (10), e14149. https://doi.org/10.2196/14149.

Krittanawong, C., Maitra, N.S., Qadeer, Y.K., Wang, Z., Fogg, S., Storch, E.A., Celano, C. M., Huffman, J.C., Jha, M., Charney, D.S., Lavie, C.J., 2023. Association of depression and cardiovascular disease. Am. J. Med. 136 (9), 881–895. https://doi.org/10.1016/j.amjmed.2023.04.036.

Lee, Y., Ragguett, R.-M., Mansur, R.B., Boutilier, J.J., Rosenblat, J.D., Trevizol, A., Brietzke, E., Lin, K., Pan, Z., Subramaniapillai, M., Chan, T.C.Y., Fus, D., Park, C., Musial, N., Zuckerman, H., Chen, V.C.-H., Ho, R., Rong, C., McIntyre, R.S., 2018. Applications of machine learning algorithms to predict therapeutic outcomes in depression: a meta-analysis and systematic review. J. Affect. Disord. 241, 519–532. https://doi.org/10.1016/j.jad.2018.08.073.

LeVasseur, A.L., 2021. Effects of social isolation on a long-term care resident with dementia and depression during the COVID-19 pandemic. Geriatric Nursing (New York, N.Y.) 42 (3), 780–781. https://doi.org/10.1016/j.gerinurse.2021.04.007.

Li, Y., Wu, Y., Zhai, L., Wang, T., Sun, Y., Zhang, D., 2017. Longitudinal association of sleep duration with depressive symptoms among middle-aged and older Chinese. Sci. Rep. 7 (1), 11794. https://doi.org/10.1038/s41598-017-12182-0.

Li, H., Liu, X., Zheng, Q., Zeng, S., Luo, X., 2022. Gender differences and determinants of late-life depression in China: a cross-sectional study based on CHARLS. J. Affect. Disord. 309, 178–185. https://doi.org/10.1016/j.jad.2022.04.059.

Lin, S., Wu, Y., He, L., Fang, Y., 2023. Prediction of depressive symptoms onset and long-term trajectories in home-based older adults using machine learning techniques. Aging Ment. Health 27 (1), 8–17. https://doi.org/10.1080/13607863.2022.2031868.

Liu, B.-P., Jia, C.-X., 2023. The associations of physical activity and lifetime depression with all-cause and cause-specific mortality: evidence from a prospective cohort study. Psychiatry Res. 324, 115206. https://doi.org/10.1016/j.psychres.2023.115206.

Lokuge, S., Frey, B.N., Foster, J.A., Soares, C.N., Steiner, M., 2011. Depression in women: windows of vulnerability and new insights into the link between estrogen and serotonin. J. Clin. Psychiatry 72 (11), e1563–e1569. https://doi.org/10.4088/JCP.11com07089.

Lu, J., Xu, X., Huang, Y., Li, T., Ma, C., Xu, G., Yin, H., Xu, X., Ma, Y., Wang, L., Huang, Z., Yan, Y., Wang, B., Xiao, S., Zhou, L., Li, L., Zhang, Y., Chen, H., Zhang, T., Zhang, N., 2021. Prevalence of depressive disorders and treatment in China: a cross-sectional epidemiological study. Lancet Psychiatry 8 (11), 981–990. https://doi.org/10.1016/S2215-0366(21)00251-0.

Luik, A.I., Zuurbier, L.A., Direk, N., Hofman, A., Van Someren, E.J.W., Tiemeier, H., 2015. 24-hour activity rhythm and sleep disturbances in depression and anxiety: a population-based study of middle-aged and older persons. Depress. Anxiety 32 (9), 684–692. https://doi.org/10.1002/da.22355.

Lyall, L.M., Sangha, N., Zhu, X., Lyall, D.M., Ward, J., Strawbridge, R.J., Cullen, B., Smith, D.J., 2023. Subjective and objective sleep and circadian parameters as predictors of depression-related outcomes: A machine learning approach in UK Biobank. J. Affect. Disord. 335, 83–94. https://doi.org/10.1016/j.jad.2023.04.138.

Nielson, S.A., Kay, D.B., Dzierzewski, J.M., 2023. Sleep and depression in older adults: a narrative review. Curr. Psychiatry Rep. 25 (11), 643–658. https://doi.org/10.1007/s11920-023-01455-3.

Nisar, A., Yin, J., Waqas, A., Bai, X., Wang, D., Rahman, A., Li, X., 2020. Prevalence of perinatal depression and its determinants in Mainland China: a systematic review and meta-analysis. J. Affect. Disord. 277, 1022–1037. https://doi.org/10.1016/j.jad.2020.07.046.

Niu, L., Yao, C., Zhang, C., Zhou, C., Fu, Y., Li, Y., Yang, H., Sun, X., Yang, J., Zhao, P., Yi, S., Wang, T., Li, S., Li, J., 2023. Sex- and age-specific prevalence and risk factors of depressive symptoms in Parkinson's disease. J. Neural Transm. 130 (10), 1291–1302. https://doi.org/10.1007/s00702-023-02658-x.

Orrù, G., Pettersson-Yeo, W., Marquand, A.F., Sartori, G., Mechelli, A., 2012. Using Support Vector Machine to identify imaging biomarkers of neurological and psychiatric disease: a critical review. Neurosci. Biobehav. Rev. 36 (4), 1140–1152. https://doi.org/10.1016/j.neubiorev.2012.01.004.

Pan, C., Liu, L., Cheng, S., Yang, X., Meng, P., Zhang, N., He, D., Chen, Y., Li, C., Zhang, H., Zhang, J., Zhang, Z., Cheng, B., Wen, Y., Jia, Y., Liu, H., Zhang, F., 2023. A multidimensional social risk atlas of depression and anxiety: an observational and genome-wide environmental interaction study. J. Glob. Health 13, 04146. https://doi.org/10.7189/jogh.13.04146.

Potter, J.R., Yoon, K.L., 2023. Interpersonal factors, peer relationship stressors, and gender differences in adolescent depression. Curr. Psychiatry Rep. 25 (11), 759–767. https://doi.org/10.1007/s11920-023-01465-1.

Riemann, D., Krone, L.B., Wulff, K., Nissen, C., 2020. Sleep, insomnia, and depression. Neuropsychopharmacology: Official Publication of the American College of. Neuropsychopharmacology 45 (1), 74–89. https://doi.org/10.1038/s41386-019-0411-y.

Rudnicka, E., Napierała, P., Podfigurna, A., Męczekalski, B., Smolarczyk, R., Grymowicz, M., 2020. The World Health Organization (WHO) approach to healthy ageing. Maturitas 139, 6–11. https://doi.org/10.1016/j.maturitas.2020.05.018.

Sau, A., Bhakta, I., 2017. Predicting anxiety and depression in elderly patients using machine learning technology. Healthcare Technology Letters 4 (6), 238–243. https://doi.org/10.1049/htl.2016.0096.

Simjanoski, M., Ballester, P.L., da Mota, J.C., De Boni, R.B., Balanzá-Martínez, V., Atienza-Carbonell, B., Bastos, F.I., Frey, B.N., Minuzzi, L., Cardoso, T. de A., Kapczinski, F., 2022. Lifestyle predictors of depression and anxiety during COVID-19: a machine learning approach. Trends Psychiatry Psychother. 44, e20210365. https://doi.org/10.47626/2237-6089-2021-0365.

Song, T., Han, X., Du, L., Che, J., Liu, J., Shi, S., Fu, C., Gao, W., Lu, J., Ma, G., 2018. The role of neuroimaging in the diagnosis and treatment of depressive disorder: a recent review. Curr. Pharm. Des. 24 (22), 2515–2523. https://doi.org/10.2174/1381612824666180727111142.

Stenwig, E., Salvi, G., Rossi, P.S., Skjærvold, N.K., 2022. Comparative analysis of explainable machine learning prediction models for hospital mortality. BMC Med. Res. Methodol. 22, 53. https://doi.org/10.1186/s12874-022-01540-w.

Ten Have, M., de Graaf, R., van Dorsselaer, S., Tuithof, M., Kleinjan, M., Penninx, B.W.J. H., 2018. Recurrence and chronicity of major depressive disorder and their risk indicators in a population cohort. Acta Psychiatr. Scand. 137 (6), 503–515. https://doi.org/10.1111/acps.12874.

Udeh-Momoh, C.T., Watermeyer, T., Sindi, S., Giannakopoulou, P., Robb, C.E., Ahmadi-Abhari, S., Zheng, B., Waheed, A., McKeand, J., Salman, D., Beaney, T., de Jager Loots, C.A., Price, G., Atchison, C., Car, J., Majeed, A., McGregor, A.H., Kivipelto, M., Ward, H., Middleton, L.T., 2021. Health, lifestyle, and psycho-social determinants of poor sleep quality during the early phase of the COVID-19 pandemic: a focus on UK older adults deemed clinically extremely vulnerable. Front. Public Health 9, 753964. https://doi.org/10.3389/fpubh.2021.753964.

Uher, R., Payne, J.L., Pavlova, B., Perlis, R.H., 2014. Major depressive disorder in Dsm-5: implications for clinical practice and research of changes from Dsm-Iv. Depress. Anxiety 31 (6), 459–471. https://doi.org/10.1002/da.22217.

United Nations, Department of Economic and Social Affairs, Population Division, 2022. World Population Prospects 2022: Summary of Results. UN DESA/POP/2022/TR/NO. 3.

Unützer, J., Katon, W., Callahan, C.M., Williams Jr., J.W., Hunkeler, E., Harpole, L., Hoffing, M., Della Penna, R.D., Noël, P.H., Lin, E.H., 2002. Collaborative care management of late-life depression in the primary care setting: a randomized controlled trial. Jama 288 (22), 2836–2845.

Van Lente, E., Barry, M.M., Molcho, M., et al., 2012. Measuring population mental health and social well-being. Int. J. Public Health 57, 421–430. https://doi.org/10.1007/s00038-011-0317-x.

Wang, R., Feng, Z., Liu, Y., Lu, Y., 2020. Relationship between neighbourhood social participation and depression among older adults: a longitudinal study in China. Health Soc. Care Community 28 (1), 247–259. https://doi.org/10.1111/hsc.12859.

Wang, W., Liu, Y., Ji, D., Xie, K., Yang, Y., Zhu, X., Feng, Z., Guo, H., Wang, B., 2024. The association between functional disability and depressive symptoms among older adults: findings from the China Health and Retirement Longitudinal Study (CHARLS). J. Affect. Disord. 351, 518–526. https://doi.org/10.1016/j.jad.2024.01.256.

Williams, M.W., Li, C.-Y., Hay, C.C., 2020. Validation of the 10-item Center for Epidemiologic Studies Depression Scale Post Stroke. Journal of Stroke and Cerebrovascular Diseases: The Official Journal of National Stroke Association 29 (12), 105334. https://doi.org/10.1016/j.jstrokecerebrovasdis.2020.105334.

Xiao, M., Wang, Q., Ren, W., Zhang, Z., Wu, X., Wang, Z., Feng, L., Chen, S., He, J., 2018. Impact of prediabetes on poststroke depression in Chinese patients with acute ischemic stroke. Int. J. Geriatr. Psychiatry 33 (7), 956–963. https://doi.org/10.1002/gps.4878.

Yang, Y., Hou, D.L., 2024. Association of depressive symptoms and dementia among middle-aged and elderly community-dwelling adults: results from the China Health and Retirement Longitudinal Study (CHARLS). Acta Psychol. 243, 104158. https://doi.org/10.1016/j.actpsy.2024.104158.

Zhang, X., Bellolio, M.F., Medrano-Gracia, P., Werys, K., Yang, S., Mahajan, P., 2019. Use of natural language processing to improve predictive models for imaging utilization in children presenting to the emergency department. BMC Med. Inform. Decis. Mak. 19 (1), 287. https://doi.org/10.1186/s12911-019-1006-6.

Zhao, Yaohui, Strauss, John, Chen, Xinxin, Wang, Yafeng, Gong, Jinquan, Meng, Qinqin, Wang, Gewei, Wang, Huali, 2020. China Health and Retirement Longitudinal Study Wave 4 User's Guide. Peking University, National School of Development.

Zhou, L., Ma, X., Wang, W., 2021. Relationship between cognitive performance and depressive symptoms in chinese older adults: the China Health and Retirement Longitudinal Study (CHARLS). J. Affect. Disord. 281, 454–458. https://doi.org/10.1016/j.jad.2020.12.059.