Artificial Intelligence Modeling of Mood, Coping, Work Engagement and Social Factors in Predicting Mental Health Outcomes

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Abstract. Mental health conditions currently account for approximately 14 percent of the global disease burden, according to the World Health Organization, while depression will be the leading cause of disability by 2030. This developing crisis underlines the pressing need to ascertain behavioral and psychological markers associated with mental health risks. This study investigates psychosocial determinants of self-reported mental health history by analyzing a large-scale publicly available behavioral dataset comprising 292,364 individual observations. Artificial Intelligence (AL) based machine learning logistics Modeling framed in this study with self-reported mental status as response variable and four key psychosocial predictors: Mood Swings, Coping Struggles, Work Interest and Social Weakness as independent variables. Initial bivariate models indicated significant associations between Mood Swings and Coping Struggles and the likelihood of reporting mental health conditions. In the final logistic model, Mood Swings ($p < 2e-16$, T value: 17.61) and Work Interest ($p < 2e-16$, T value: 31.48) emerged as the most significant positive predictors, while Social Weakness showed a statistically significant negative association. VIF scores indicated no multicollinearity among the predictors. Further, gender-stratified modeling framed by this current study showed striking differences in predictor behavior between male and female respondents; this is especially true for social functioning, which appeared positively significant in females but negatively significant in males, and for coping mechanisms, which appeared much stronger in females. These findings point toward the important role of emotional regulation, managing of stress, vocational engagement, and interpersonal dynamics in shaping mental health outcomes. This brings into evidence the optimal threshold on the ROC curve, depicting that about 70.4% of the actual positive cases of mental health are correctly identified by the model. The logistic model slightly outperformed and revealed that AI can be used to predict mental health risks.

Keywords: Artificial Intelligence Modeling, Mood Swings, Coping Mechanisms, Mental Health, Psychosocial Predictors, Behavioral Analysis.

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1 Introduction

Mental health disorders continue to rise worldwide and affect millions, regardless of age or background [1]. Understanding behaviors and emotions that shape mental health is important to support early diagnosis, improve treatment and inform public health systems about better service planning. Poor emotional control, weak coping skills and social difficulties have been shown by research to heighten the risk of mental illness [2, 3]. Mood swings, stress and low social support are linked to anxiety and depression [4]. A loss of interest in work or daily activities is another frequent warning sign often related to burnout or depression [5]. Although these links are much clearer now large-scale studies that utilize real-world data remain limited. More research is needed to explore how these behavioral traits considered together influence mental health history. Logistic regression was chosen for this study because it’s easy to interpret and helps show how each factor influences the outcome something especially important in healthcare and social sciences where understanding why something happens matters as much as predicting it. A gradient boosting model was also tested to see if a more complex approach could offer better performance.

2 Literature Review

Much research has gone into studying how psychological traits influence outcomes regarding mental health. Many studies try to find out behavioral markers which with various degrees of accuracy can predict problems regarding mental health especially anxiety, depression and mood disorders. Work interest or vocational engagement is increasingly considered to be a marker for good mental health. Lack of desire to undertake work-related activities or lack of motivation towards them may be an indicator of psychological issues such as burnout, depression, or chronic fatigue syndrome [6]. Bianchi et al. discovered a strong association between professional disengagement and more symptoms of depression in white-collar employees. This would suggest that the relation is bidirectional [7].

Another factor highly associated with deteriorating mental health is social weakness, which involves things such as withdrawal from social situations, poor communication, and low levels of support from other individuals. Individuals who feel isolated from others or that they do not belong are highly vulnerable to having problems with their mental health and recovering poorly from conditions affecting their mental health [8]. Coping difficulties, generally characterized by how individuals cannot handle their psychological stress well, also play a very important role in mental health studies. Coping strategies may be considered a bridge connecting being stressed and developing psychological problems. Various forms of maladaptive coping include avoidance, denial, and emotional suppression, all of which have been associated with increased symptoms of anxiety, depression, and substance use disorders [9, 10]. On the contrary, adaptive coping involves solving problems and seeking help from others, which is found to protect one from mental distress.

People often say that mood swings, or affective instability, are early signs of mood and personality disorders. Their presence is strongly linked to depression, bipolar disorder, and emotional dysregulation, especially in teens and young adults [11]. Longitudinal studies have shown that having mood swings that happen often and are very strong can change more likely to have both internalizing and externalizing psychological symptoms [12]. On the other hand, social support networks are protective factors that help people stay strong in the face of emotional distress [13]. In recent years, machine learning has also been applied to predict mental health conditions using diverse behavioral data. These models have shown promising accuracy especially in identifying depression and anxiety patterns from self-reported and sensor-based inputs [14].

3 Research Gaps

- Limited Integration of Multiple Psychosocial Predictors:
  While previous studies have investigated individual psychological traits such as mood swings, coping mechanisms, or social functioning in relation to mental health disorders, few have modeled the combined influence of these variables in a single unified statistical framework. The current study fills this gap by simultaneously analyzing multiple psychosocial predictors using a multivariate regression approach.
- Lack of Large-Scale, Real-World Behavioral Data:
  Most existing research is based on small clinical or survey-based samples (often under a few thousand participants), limiting generalizability. This study utilizes a massive dataset of 292,364 samples, offering statistically robust insights with broader applicability across populations.
- Underutilization of the robust AI modeling powers for Mental Health Prediction:
  Although there is an increasing application of machine learning techniques on mental health prediction, traditional GLMs have remained underutilized for interpreting behavioral predictors in large datasets.
- Inadequate Emphasis on Work Interest and Social Deficiency:
  Whereas both mood and coping have received a great deal of attention, work-related motivation (Work Interest) and social behaviour (Social Weakness) have been relatively understudied as predictors of mental health history.
- Limited evidence of the significance of the predictors and multicollinearity for the mental health models:
  Few studies rigorously assess the individual contribution and independence of predictors. This paper does this by computing t-values, p-values, and VIFs to confirm the significance and absence of multicollinearity, hence guaranteeing that the model is statistically sound.

Previous studies on mental health prediction have often emphasized black-box machine learning approaches such as neural networks and support vector machines [14]. These models have limited interpretability which is crucial for psychological and clinical insights, even though they can achieve higher predictive accuracy. On the other hand, the main framework used in this study is logistic regression which makes it possible to clearly estimate the independent contribution of each psychosocial predictor. Here gradient boosting is only used for benchmarking; interpretable modeling that can direct actual mental health assessment is still the main focus.

3.1 Research Objectives

The primary objective of this study is to evaluate the influence of key psychosocial variables Mood Swings, Coping Struggles, Work Interest and Social Weakness on self-reported mental health history using a large-scale behavioral dataset. Specifically, the study aims to:

- Quantify the gender wise, individual and combined effects of selected psychological predictors on mental health outcomes using optimized AI Modeling
- Identify statistically significant behavioral indicators of the build model that can serve as early warning signs for mental health risks.
- Assess multicollinearity and model robustness to ensure statistical reliability and interpretability of the predictors.

4 Research Methodology

In order to examine the connection between important psychosocial predictors and mental health history this study uses a quantitative, cross-sectional research design. The behavioral factors influencing self-reported mental health conditions in a large population dataset were examined using statistical modeling.

4.1 Data Collection

All records are anonymized, which ensures that ethical research standards are met and the study can be fully reproduced. The dataset used for this project includes 292,364 anonymized records with 17 features collected from a publicly available real-world behavioral assessment platform [15]. Each record includes responses to structured questions on mood fluctuations, coping behavior, work-related motivation, and social functioning. The outcome variable, MT_History, is a binary indicator reflecting the presence or absence of a self-declared history of mental health conditions. All data were cleaned and preprocessed to remove incomplete or inconsistent entries. Hot encoding were done to convert categorical Text values into corresponding binary form (1 of Yes and 0 for No). Following significant attributes are extracted from the dataset for Modeling and analysis purpose using attribute evaluator method which were evident more impactful for the Modeling of mental health status as outcome variable.

Variables and Operational Definitions

Dependent Variable:

MT_History: Binary outcome variable (1 = self-reported mental health history, 0 = no history).

Independent Variables:

Mood_Swings: Frequency and intensity of emotional fluctuations.

Coping_Struggles: Difficulty in managing stress or negative emotions.

Work_Interest: Level of motivation and engagement in professional tasks.

Social_Weakness: Indicators of social withdrawal or poor interpersonal functioning.

4.2 Model Design

In this section, various machine learning models were framed with significant predictors from the dataset to inspect their associations for modeling Mental Health History of the respondents.

4.2.1 Logistic Regression Modeling:

The study framed a logistic regression model [with train:70% and test: 30%] using R computing environment by taking mood swings, coping struggles, work interest and social weakness as predictive variables to find the outcome of response variable Mental Health History of respondents. The Generalized Linear Model (GLM) was framed because it is easy to understand and model binary outcomes using a logistic regression framework. The study evident that all four key predictors were significant with the response variable as indicated by 'stars' in Figure 1.

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Call:
glm(formula = MT_History ~ Mood_Swings + Coping_Struggles + Work_Interest
+Social_Weakness, family="binominal", data = MT_DB)

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.268237   0.002585 103.753  < 2e-16 ***
Mood_Swings       0.018790   0.001067  17.612  < 2e-16 ***
Coping_Struggles  0.008532   0.001721   4.958 7.13e-07 ***
Work_Interest     0.059618   0.001893  31.488  < 2e-16 ***
Social_Weakness  -0.027837   0.001863 -14.941  < 2e-16 ***
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Fig. 1. GLM Coefficients for Predictors of Mental Health

The model evident that Work_Interest has the largest effect size (positive) where as Social_Weakness has a significant negative effect. Overall, all predictors are individually significant to the response variable MT_History. Dispersion parameter: 0.2156 closer to 1 indicates a well-fitting Gaussian model. The strong positive associations of Mood Swings and Work Interest with MT_History suggest that emotional instability and changes in vocational engagement are significant behavioral indicators of mental health conditions. Interestingly the Social Weakness variable had a negative coefficient, suggesting that one who reports lower social strength is less likely to report a history of mental health which is counterintuitive. Further research can be done to tap into cultural or contextual meaning given to social functioning. The VIF for all predictors was less than 1.02, thus indicating low multicollinearity which in turn justifies the statistical validity of the model as listed below:

Mood_Swings: 1.0086 || Coping_Struggles: 1.0008 || Work_Interest: 1.0046 || Social_Weakness: 1.0127

These values confirm that no predictor is redundant or overly correlated with others.

4.2.2 Gender-Based Stratified Modeling:

To explore any possible gender-based differences in psychological risk factors, the dataset was stratified by gender and separate GLMs fitted for male and female (male = 239,850 || female = 52,514) subsets using the same predictors.

These findings hint that behavioral pathways to mental health risk diverge by gender: whereas mood and coping are strong predictors for females, the effect of social weakness is dichotomous in increasing the risk in females and decreasing it in males. This could be an indication of gendered coping strategies, expectations or cultural factors in the expression of psychological distress.

- Mood Swings and Coping Struggles had greater predictive power among females, indicating a heightened sensitivity to emotional and stress-related behaviors in this group.
- Social Weakness showed opposite effects positively associated with MT_History in females but negatively in males. This may reflect gendered differences in social expression or reporting and warrants further psychological and sociocultural exploration.
- Work Interest remained a strong and consistent indicator for both genders, reinforcing its value as a cross-gender marker for mental well-being.

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.279162	0.002841	98.269	< 2e-16	***
Mood_Swings	0.017651	0.001186	14.889	< 2e-16	***
Coping_Struggles	0.005680	0.001906	2.979	0.00289	**
Work_Interest	0.059335	0.002106	28.170	< 2e-16	***
Social_Weakness	-0.041443	0.002065	-20.066	< 2e-16	***

Male

Coefficients:

	Estimate	Std. Error	t value	Pr (>|t|)	
(Intercept)	0.219652	0.006332	34.691	< 2e-16	***
Mood_Swings	0.022609	0.002473	9.141	< 2e-16	***
Coping_Struggles	0.023100	0.004053	5.699	1.21e-08	***
Work_Interest	0.060582	0.004334	13.978	< 2e-16	***
Social_Weakness	0.032308	0.004326	7.468	8.29e-14	***

Female

Fig. 2. Gender-Based Logistic Modeling for Finding Impact of Predictors

Table 1. Gender Specific Model Comparison

Predictor(s)	**Female Estimate**	**Male Estimate**	**Direction (Female vs Male)**	**Notable Differences**
(Intercept)	0.220	0.279	Higher in Males	Suggests higher baseline Mental History in males
Mood_Swings	0.023	0.018	Stronger in Females	Highly significant in both
Coping_Struggles	0.023	0.006	Much stronger in Females	Statistically significant in both
Work_Interest	0.061	0.059	Very similar	Strong predictor for both sexes
Social_Weakness	0.032	-0.041	Opposite directions	Positive in females, negative in males

The comparison of gender specific Modeling result are depict in Table 1 which indicates how the four predictors affect men and women differently. The starting point (intercept) is higher for men. This means men, in general, had a slightly higher chance of reporting mental health history. Mood Swings and Coping Struggles had stronger effects in women. This means women were more affected by emotional ups and downs and stress. Work Interest had a similar effect for both men and women. It was a strong predictor in both cases. The biggest difference was in Social Weakness. For women, it increased the chance of mental health issues. But for men, it showed the opposite effect. This may be because men and women report or experience social problems differently. Overall Work Interest was a strong and clear predictor in both groups.

4.3 Model Evaluation

The predictive GLM model with 70% train and 30% test data evident a moderate fit model with Area under the curve: 0.5215. The Breusch-Pagan test and tuning further performed on the model to optimal threshold value and Sensitivity (True Positive Rate): 0.7042594, means, the model correctly identifies about 70.4% of the actual positive cases. The Specificity (True Negative Rate) of the model is 0.3593119 means, the model correctly identifies only 35.9% of the actual negative cases. Despite of the moderate level of performance matrix, the study able to model the complex association of various significant Psychosocial predictors for mental health detection from self-reported heterogeneous respondents dataset where either they not disclose all their mental health related issues or not able to express correctly those issues. The study also revealed the following point:

- No clear pattern or funnel shape (As shown in Figure 3a), suggests that the assumption of homoscedasticity is fair.
- No systematic curvature indicates that the linearity assumption is also likely valid.
- No clustering or outlier influence is immediately visible, which is good side of the model.

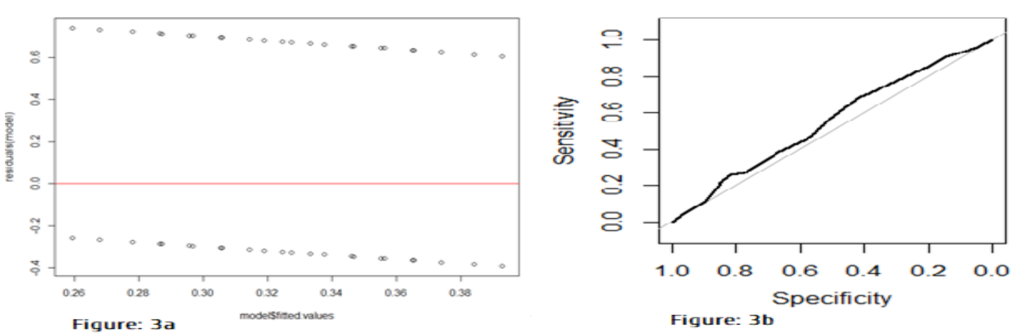

Fig. 3. Breusch-Pagan Test Plot and ROC Curve of the Model

Finally, a cross checking were also conducted by framing a gradient boosting model with same Train-Test-validation data with same predictors and response variable. The comparison of logistic and gradient boosting method result revealed that for both the model, RMSE is 0.46 but ROC for gradient boosting model slightly better 0.5686 over the logistic regression model.

5 Discussion, Interpretation and Implications

All four predictors were significant, but the initial logistic model still showed low predictive power (AUC ~0.52–0.57). This may be due to several reasons. The data came from self-reported responses, which can be biased, incomplete and many cases patients not able to express accurately their mental health states. The model also used only four psychosocial factors, while mental health depends on many other things like biology, environment, and demographics. In addition, the outcome was a simple yes/no report of mental health history, which does not capture severity or range. These limits together reduced accuracy, even though the below predictors were statistically important as found through ranker and best first methods of attribute selection. The interpreted summary of Table 1 is listed below.

- Mood swings are a strong sign of psychological instability. People with frequent emotional changes are more likely to report past mental health problems. This shows mood swings can be an early warning sign.
- Coping struggles also have a positive link, though weaker than mood swings. This highlights that poor stress management increases mental health risk for both men and women.
- Work interest has the strongest positive effect. A drop in interest or motivation at work may point to hidden psychological distress, such as depression, burnout, or loss of pleasure.
- There is a negative correlation between social weakness and men. This outcome might appear out of the ordinary. Men's interpretation of social functioning in surveys, cultural stigma, or reporting bias could be the cause. It might also mean that men don't openly express their distress because they get more support or express it in other ways.

The analysis indicates that behavioral patterns like a decline in work interest can forecast mental health problems in both genders. It also discovers that social vulnerability impacts genders in distinct ways indicating that gender roles might influence how individuals perceive and communicate about mental health. These findings may result in enhanced mental health evaluations that recognize important behaviors and consider gender disparities. The results emphasize the significance of remaining involved at work and preserving social ties, suggesting that initial assistance should prioritize these elements.

6 Conclusion

This study seeks to analyze the relationship between behavioral and psychological factors and self-reported mental health history using a very large and diverse data set. Using a Generalized Linear Model it examined how four major psychosocial factors are related to mental health outcomes, namely mood swings, difficulties in coping, loss of interest in work, and social vulnerability. The results indicated that mood swings and loss of work interest are strong predictors of potential mental health challenges. Social weakness however showed a surprisingly negative relation, reflecting the fact that cultural or social features impact the way respondents report or perceive this trait. Several gender-specific analyses that have been highlighted evinced clear differences in the behavior of the predictors studied, again pointing to the importance of gender when studying mental health or designing interventions. Because these predictors did not overlap in such a way as to distort the analysis, the model here offers sound insight into the unique role which each behavioral factor plays. Overall findings support the view that self-reported psychological traits may have a place as meaningful predictors of mental health risk. They also point out the potential for developing scalable, data-driven tools that could serve to identify early warning signs and enable earlier mental health screening and prevention. Future research incorporating longitudinal, clinical, and demographic data can further enhance the precision and applicability of such predictive frameworks.

7 Limitations and Future Research Scope

7.1 Limitations

- Cross-Sectional Design: The cross-sectional nature of the data utilized in this study makes it more difficult to determine the causal relationships between the psychological predictors and mental health history. To prove causation and temporality, longitudinal data would be necessary.
- Self-Reported Variables: Since all predictor variables, such as social behavior, coping difficulties and mood swings are probably self-reported there may be reporting bias and subjectivity in the answers.
- Absence of Clinical Diagnosis: Because the analysis is based on self-reported mental health history rather than clinical diagnoses, mental health conditions may be overreported or underreported.
- Exclusion of Demographic Variables: The model fails to incorporate demographic covariates such as age, gender, socioeconomic status or educational attainment, which may affect mental health and interact with psychological characteristics.
- Static Modeling Technique: Generalized Linear Models (GLMs) are easy to understand but they might not be able to find nonlinear or hierarchical relationships that more advanced machine learning models (like random forests and neural networks) can.
- The ROC value for the model developed in this study is 0.55 and the Root Mean Square Error value is 0.46. These values are moderate. The moderate performance in modeling is comprehensible, as in self-reported instances, respondents frequently either fail to disclose or are unable to articulate their genuine mental health status.

7.2 Future Research Scope

- Future research should follow individuals over long periods to observe behavioral changes and understand causal mechanisms linking psychological traits and mental health.
- Studies should include a wider range of variables demographic, biological and environmental to improve explanatory power and provide a fuller picture of mental-health influences.
- Behavioral data should be merged with clinically validated mental-health records to increase accuracy and reduce measurement bias.

- Researchers should explore advanced modeling techniques, such as nonlinear models, ensemble methods and interpretable models like explainable boosting machines, to uncover deeper patterns while maintaining interpretability.
- Study findings can support the development of predictive tools such as digital screening or risk-assessment systems enabling more personalized early interventions.
- Larger more diverse samples and long-term study designs are needed to confirm the reliability of results and determine whether observed effects persist over time.
- These steps help ensure that predictive findings can be translated into actionable insights for effective policy-making and mental-health interventions.

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