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AI-Driven Mobile Application for Self-Monitoring Personalized Premenstrual Symptoms and Risk Assessment of Depressive Crises in Female University Students

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Abstract

Premenstrual Syndrome (PMS) and depressive symptoms are common concerns for female university students, often triggered by hormonal fluctuations before menstruation. These conditions can severely impact academic performance, interpersonal relationships, and overall well-being, particularly when symptoms escalate into severe depressive episodes. Even though the prevalence, awareness, and self-management strategies among students are on the rise, they remain limited, particularly in cultural contexts where women's health and emotional well-being receive little attention. This study presents the development of an AI-driven mobile application designed to facilitate personalized tracking of premenstrual symptoms and assess the risk of depressive episodes. The application integrates machine learning models trained on self-reported psychological and physiological data, using validated instruments such as DASS-21 and PSST-A. The research adopted a mixed-methods approach, involving survey-based symptom identification, model training and validation, system design, and user satisfaction evaluation. This research contributes to the development of artificial intelligence-assisted self-care technology for the purpose of monitoring personal health and taking preventative psychological measures. The findings indicate that the application that was developed is beneficial in terms of forecasting the likelihood of someone suffering from depression and fostering self-awareness regarding mental health among college students. Considering this, the system has the potential to develop into a useful tool for providing aid to female students attending universities.

Keywords: AI for Healthcare, Depressive Crisis Risk Monitoring, Medical Data Analytics, Medical Informatics, Personalized Premenstrual Symptom

1. Introduction

A depressive crisis describes an intense psychological state characterized by a sudden and severe escalation of depressive symptoms, markedly different from typical depressive episodes in both intensity and urgency. While major depressive episodes, defined in the DSM-5, require at least two weeks of persistent low mood or anhedonia along with functional impairments, a depressive crisis is a more immediate and disruptive event. People often report feelings of extreme hopelessness, cognitive shutdown, inability to perform daily activities, and active suicidal thoughts. These crises may require emergency psychiatric treatment and represent a critical point in mental health [1], [2]. Conceptually, the term aligns with crisis models used in psychology and suicidology, where increased risk necessitates quick assessment and specialized care [3]. Differentiating depressive crises from general depression is vital for targeted intervention, especially among vulnerable groups such as female university students facing many pressures on body, mind, learning, and other areas, including menstruation and Premenstrual Syndrome (PMS).

PMS is a common health issue among women of reproductive age, particularly in the days leading up to menstruation when hormonal fluctuations affect physical, emotional, and behavioral aspects. Emotional and behavioral symptoms such as tension, anxiety, depression, mood swings, irritability, insomnia, and social isolation can significantly impact a woman's quality of life and learning efficiency. For university students, who face additional stress from academic responsibilities, social adjustments, and physical changes, PMS can further hinder academic performance, relationships, and mental well-being if not properly managed. However, many students lack access to crucial

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knowledge and self-care strategies, especially within Thai society, where there are still societal constraints on openly discussing sexual health and women's issues. [4], [5], [6].

Moreover, depression among adolescents and university students is a mental health problem that is continuously increasing in severity [7]. It is triggered by stress from studying, social changes, and emotional fluctuations, which often manifest in ways that are not noticed or treated on time, especially in women, whose mood and behavior closely relate to changes in sex hormones [8]. Particularly in the period before menstruation, PMS can negatively affect both the body and mind. Symptoms related to mental health, including depressed mood, irritability, anxiety, insomnia, feelings of loneliness, and decreased concentration, can escalate into a "depressive crisis" in some cases, significantly impacting schoolwork, interpersonal relationships, and overall quality of life [9].

However, awareness and management of these conditions among female university students remain critically low [10], especially in the context of Thai society, where discussions about emotional health and menstruation are sensitive topics [11]. As a result, many face challenges without the tools or guidance to monitor and care for themselves effectively. Consequently, it is essential to develop methodologies incorporating modern technology, especially information technology and AI, to help track, analyze, and predict symptoms related to individual students' menstrual cycles. These methods can facilitate effective notifications, health guidance, and the promotion of self-care practices [12]. Therefore, this research seeks to analyze the issues and characteristics of premenstrual emotional and behavioral symptoms among female students. The initiative aims to develop self-care guidelines that leverage artificial intelligence technology to predict symptoms and mitigate the effects of these conditions, thereby improving the long-term physical and mental health of female students.

The primary research objective is to develop a mobile application that uses mobile technology and AI to offer personalized monitoring of premenstrual symptoms and predict the likelihood of depressive episodes. The secondary goals are to look at how premenstrual emotional and depressive symptoms vary and how severe they are in female university students, build a model to predict the risk of depressive episodes based on individual symptoms, create a mobile app that uses AI for tracking symptoms, and assess how well the app works and how easy it is to use for emotional self-care. This research aims to create a tool that enhances mental health management by providing early detection of depressive episodes and empowering users with resources for emotional well-being.

2. Literature Reviews

Digital technologies have reshaped preventive mental health care, especially for high-risk groups like female university students. The study, "AI-Driven Mobile Application for Self-Monitoring Personalized Premenstrual Symptoms and Risk Assessment of Depressive Crises in Female University Students," is important because it focuses on the connection between premenstrual symptoms and depression, which is a serious but often ignored problem among students. Despite the high prevalence of depression and anxiety in this group, many cases go undiagnosed due to stigma, limited access, and lack of awareness [13]. This mobile app empowers students to self-monitor, enhancing awareness and enabling early detection of mental health risks. The approach aligns with modern public health strategies that emphasize prevention over reaction. Prior research, such as Clough et al., [14] has shown that mobile self-help apps can significantly reduce anxiety and rumination, offering simple, scalable, and real-time tools tailored to individual needs. This personalized aspect is crucial for conditions like PMDD, where hormonal shifts exacerbate mental health challenges. Digital solutions that integrate biological and emotional data engage users more effectively and yield better outcomes than traditional methods. Thus, this study strengthens the case for technology-based prevention and shows that mobile apps can go beyond tracking—they can actively prevent the onset of depressive disorders [15].

The application leverages mobile technology to deliver a personalized health monitoring experience by offering tailored feedback based on premenstrual symptoms reported by users. This aligns with the AI4U project [16], which emphasizes user-centered development in AI-based mental health applications for young people. To ensure clinical reliability, the app incorporates validated psychological tools like DASS-21 and PSST-A. Personalized health monitoring via mobile apps is increasingly vital, especially for chronic conditions and menstrual-related symptoms. By allowing users to track mood, symptoms, and physiological data, the app enhances engagement and clinical relevance. Studies show that user-centered design significantly improves adoption and effectiveness, particularly among younger demographics [17]. The combination of user-reported information with standard tests helps AI analyze mental health risks by looking at past patterns and current data [18]. This approach is especially suitable for university students—tech-savvy yet vulnerable to stress. The app's focus on cyclical, hormone-linked symptoms exemplifies personalized care and supports the broader movement toward precision medicine and digital therapeutic systems.

AI algorithms, particularly Machine Learning (ML) models, can process extensive behavioral, physiological, and self-reported data to detect patterns indicative of psychological distress. In this context, AI analyzes premenstrual symptom data alongside standardized assessments like DASS-21 and PSST-A to enable real-time evaluation of depression risk. This approach aligns with the shift toward data-informed mental health care, where AI insights augment—rather than replace—clinical judgment [19]. Recent studies show AI-based mental health tools can match clinicians in diagnosing depression and anxiety by analyzing digital behavior and language. These tools are especially valuable in underserved populations, providing scalable, accessible mental health monitoring for young adults who may avoid in-person care [20]. What makes this application particularly innovative is its focus on cyclical mental health risks linked to hormonal changes. AI enables personalized tracking and prediction of mood disorders, offering timely interventions and individualized care plans [21]. Additionally, the system's ability to continuously learn from user input enhances its adaptability, forming a dynamic feedback loop. This marks a shift from static evaluations to adaptive mental health tools that evolve alongside user behavior and environmental factors.

3. Methodology

3.1. Population and Sample Determination

3.1.1. Quantitative Data Collection

This section calculates the sample size for a population of 14,013 using Krejcie & Morgan's [22] method at a 95% confidence level with a ±5% margin of error. The table indicates 374 respondents, confirmed by the formula (χ^2 = 3.841, P = 0.5, d = 0.05). To support proportional sampling, the target was adjusted to 375 due to rounding.

Table 1. The data collected is classified by school and college.

Institutions	Data Collection Information					
	Population	%	Target	%	Collected	%
School of Agriculture and Natural Resources	469	3.35%	13	3.47%	14	3.67%
School of Allied Health Sciences	424	3.03%	11	2.93%	10	2.62%
School of Architecture and Fine Arts	524	3.74%	14	3.73%	8	2.10%
School of Business and Communication Arts	2,025	14.45%	54	14.40%	35	9.19%
School of Dentistry	97	0.69%	3	0.80%	8	2.10%
School of Education	1,443	10.30%	39	10.40%	32	8.40%
School of Energy and Environment	140	1.00%	4	1.07%	11	2.89%
School of Engineering	561	4.00%	15	4.00%	21	5.51%
School of Information and Communication Technology	674	4.81%	18	4.80%	47	12.34%
School of Law	1,122	8.01%	30	8.00%	22	5.77%
School of Liberal Arts	1,287	9.18%	34	9.07%	37	9.71%
School of Medical Sciences	918	6.55%	25	6.67%	19	4.99%
School of Medicine	293	2.09%	8	2.13%	8	2.10%
School of Nursing	417	2.98%	11	2.93%	15	3.94%
School of Pharmaceutical Sciences	521	3.72%	14	3.73%	13	3.41%

Institutions	Data Collection Information					
	Population	%	Target	%	Collected	%
School of Political and Social Science	804	5.74%	21	5.60%	23	6.04%
School of Public Health	1,981	14.14%	53	14.13%	39	10.24%
School of Science	313	2.23%	8	2.13%	19	4.99%
Total:	14,013	100.00%	375	100.00%	381	100.00%

Table 1 shows the data collection target and the actual amount collected. With permission from data owners, 6 additional participants were included. Only 375 high-quality data sets remained after data cleaning.

3.1.2. Qualitative Data Collection

In the exploratory phase, qualitative data were collected using an open-ended questionnaire to identify premenstrual female college students' mood and depressive symptoms. In this phase, contextual and behavioral components affecting mental health were uncovered to ensure clarity and relevance.

3.2. Questionnaire Development and Quality Control

The depression questionnaire examines premenstrual and menstrual depression in daily life, with sections on general information, biological data, DASS-21, PASST-A, and qualitative responses. Three experts assessed its validity, and reliability was tested and revised before final release. The results of the IOC analysis are presented in table 2.

Table 2. IOC Analysis Results

Item Statement	Expert 1	Expert 2	Expert 3	IOC Value
Section 1: General Information				
Item 1.1 What is your gender?	-1.00	-1.00	-1.00	-1.00
Item 1.2 What is your age? (in years)	1.00	1.00	1.00	1.00
Item 1.3 What is your marital status?	1.00	1.00	0.00	0.67
Item 1.4 What is your current level of study?	0.00	1.00	0.00	0.33
Item 1.5 What is your faculty or academic program?	1.00	1.00	1.00	1.00
Item 1.6 What is your living situation?	1.00	1.00	1.00	1.00
Section 2: Self-Reported Biological Data				
Item 2.1 Do you exercise regularly?	1.00	1.00	1.00	1.00
Item 2.2 Have you experienced any menstrual-related problems?	1.00	1.00	1.00	1.00
Item 2.3 At what age did you have your first menstruation (menarche)?	1.00	1.00	1.00	1.00
Item 2.4 Have you ever had sexual experience?	1.00	1.00	1.00	1.00
Item 2.5 Do you currently engage in sexual activity on a regular basis?	0.00	1.00	1.00	0.67
Item 2.6 Have you experienced menstrual-related changes after sexual activity?	1.00	1.00	1.00	1.00
Item 2.7 Have you ever used any method of contraception?	0.00	1.00	1.00	0.67

*Scoring criteria: 1 = Clearly congruent, 0 = Uncertain or unclear, -1 = Not congruent

The IOC analysis of the General Information and Biological Data sections showed most items met the acceptable threshold (IOC ≥ 0.67). Section 1 items on age, academic program, and living situation scored 1.00, while gender scored -1.00, suggesting removal. The education level question (IOC = 0.33) was considered for exclusion. In Section 2, physical activity and menstruation history had full agreement (IOC = 1.00), while sensitive questions scored 0.67, requiring refinement but were retained for analysis.

3.2.1. Preprocessing Data

Before training, the dataset underwent thorough preprocessing to handle issues common in questionnaire data, especially from DASS-21. Incomplete responses were removed, and irrelevant columns were discarded. Outliers were managed using IQR, with extreme values capped or excluded. Numerical features were standardized via Z-score normalization, while ordinal and nominal categorical variables were encoded appropriately. To mitigate class imbalance, SMOTE was applied to generate synthetic samples for minority classes. The final dataset integrated physical, emotional, and behavioral PMS-related features with psychological metrics, enabling the model to comprehend the connection between physical and mental health [23].

3.3. Development and Evaluation of Prediction Models

This study has two main parts. Stress, anxiety, and depression were used to classify depressive states using the DASS-21 [24] assessment in the first segment. The final section of the questionnaire analyzed the study group's mental health using the DASS-21 instrument, providing data for this model. The second component classified responses into PMS and PMDD to construct a predictive model for premenstrual symptoms. For this model, responses to the fourth component of the questionnaire, which comprised the PSST-A [25], were used.

This study developed models in two stages to identify the most effective approach for predicting premenstrual mental health risks. The first stage used five core machine learning algorithms—Logistic Regression, SVM, Decision Tree, K-NN, and Naïve Bayes—while the second stage applied six ensemble methods—Random Forest, Gradient Boosting, Bagging, Extra Trees, Voting, and Stacking—to enhance accuracy and reliability. The models were evaluated using 10-fold cross-validation, splitting the dataset into 10 parts for training and testing across 10 iterations to ensure reliability and generalizability. Performance metrics, including accuracy, precision, recall, and F1-score, were calculated using a confusion matrix. These metrics were critical in selecting the best model for a mobile app predicting the risk of depression linked to premenstrual symptoms.

3.4. Development of Prototype Applications

This section outlines a data-driven approach to developing an Android-based mobile app using machine learning to predict premenstrual symptoms. The app was developed using Kotlin and Java to ensure compatibility and efficiency, with the system design incorporating use cases, classes, and activity diagrams to clarify functionalities and guide development. The second principle focuses on iterative design, where prototypes are continuously created, tested, and refined based on user feedback. This approach ensures that the app is aligned with real user needs and expectations, with continuous user involvement from concept through to final testing.

3.5. Assessment of User Satisfaction

The system was tested with 30 participants on desktop and mobile platforms using a UX/UI tool to evaluate performance, usability, and user satisfaction. Qualitative feedback was collected through a questionnaire. To assess satisfaction, average scores were calculated by normalizing sub-item ratings and aggregating them by category. This method provided overall scores for each major item, helping to measure satisfaction levels and inform recommendations for future system improvements. The criteria used for scoring performance evaluation are shown in table 3.

Table 3. Criteria for Scoring Performance Evaluation

Scoring Range	Quantitative Description	Qualitative Description
4.51 – 5.00	Excellent / Strongly Acceptable	High performance, easy to use, and outstanding features
3.51 – 4.50	Very Good / Acceptable	Good performance, convenient to use, and complete features
2.51 – 3.50	Moderate / Moderately Acceptable	Acceptable performance, practical, fundamental traits
1.51 – 2.50	Fair / Low Acceptance	Poor performance, challenging usability, and lack of features
1.00 – 1.50	Needs Improvement / Unacceptable	Poor performance and difficult to use

4. Results and Discussion

4.1. Respondent Contextualization and Dimensional Analysis

This research met the study's objectives by categorizing respondents' background information into three aspects. Table 4 shows female undergraduate demographics—age, academic year, and socioeconomic status—as a baseline profile for wider applicability. The second component uses established measures to assess psychological states—depression, anxiety, and stress—relevant to menstruation patterns. Table 5 shows the results. The third examines PMS and PMDD prevalence and severity (table 4) to construct predictive machine learning models for individualized therapies.

Table 4. Characteristics of the Target Sample

Issues	Characteristics of the Target Sample			
		Respondents' year level		
1st-year level	2nd-year level	3rd-year level	4th-year level	Over 4th-year level
109 (28.61%)	81 (21.26%)	169 (44.36%)	20 (5.25%)	2 (0.52%)
		Respondents' age		
Under 19 years old	Ages 19 to 20 years	Ages 21 to 22 years	Ages 23 to 24years	Over 24 years old
37 (9.71%)	168 (44.09%)	130 (34.12%)	18 (4.72%)	28 (7.35%)
		The respondent started her menstrual cycle		
Under 10 years old	Ages 11 to 12 years	Ages 13 to 14 years	Ages 15 to 16 years	Over 16 years old
24 (6.30%)	190 (49.87%)	119 (31.23%)	44 (11.55%)	4 (1.05%)
		Respondents' sexual experiences		
	Yes		No	
	208 (54.59%)		173 (45.41%)	

Table 4 shows target sample demographics. Most respondents were third-year (44.36%), followed by first-year (28.61%) and second-year (21.26%). Few were fourth-year or higher. Nearly half (44.09%) were 19–20, followed by 21–22 (34.12). Most menstruated at 11–12 (49.87%) or 13–14 (31.23%). The majority (54.59%) reported sexual experiences. These factors contextualize the findings and ensure the sample matches the study's focus on reproductive and mental health in female university students.

Table 5. DASS-21 Assessment Outcomes

Issues	DASS-21 Assessment Outcomes				
	Normal	Mild	Moderate	Severe	Extremely Severe
Depression	188 (49.34%)	54 (14.17%)	84 (22.05%)	21 (5.51%)	34 (8.92%)
Anxiety	142 (37.27%)	61 (16.01%)	68 (17.85%)	35 (9.19%)	75 (19.69%)
Stress	206 (54.07%)	46 (12.07%)	56 (14.70%)	54 (14.17%)	19 (4.99%)

According to DASS-21 analysis, 8.92% of students reported extremely severe depression, 19.69% anxiety, and 4.99% stress (table 5). Most pupils' emotional states were normal to mild, but high-severity cases suggest early detection and tailored therapy. These data show that university students need mental health support due to academic, social, and health challenges. Monitoring emotional trends and support system efficacy requires ongoing monitoring.

Table 6 shows that 11.02% of participants met the criteria for PMDD and 43.83% for PMS, based on the PSST-A assessment tool. While more than half did not meet diagnostic thresholds, the presence of clinically significant symptoms in a subset indicates that it's time for early screening and mental health education. These results align with existing research, indicating that while mild premenstrual symptoms are common, few require clinical intervention. Targeted support, such as cognitive-behavioral strategies or professional referrals, may benefit those affected. Future research should explore contributing factors like academic stress, sleep patterns, and hormonal changes to better understand PMS severity.

Table 6. PSST-A Assessment Outcomes

Issues	PSST-A Assessment Outcomes	
	No Symptoms Found	**Found Symptoms**
Premenstrual Dysphoric Disorder (PMDD)	339 (88.98%)	42 (11.02%)
Premenstrual Syndrome (PMS)	214 (56.17%)	167 (43.83%)

4.2. Development of Machine Learning Models

This section outlines the development of machine learning models aimed at predicting mental health conditions among female university students, divided into two key tasks: predicting depressive symptoms and forecasting premenstrual conditions (PMS and PMDD). The modeling process occurred in two phases. Phase one used five standard classification algorithms—logistic regression, SVM, decision trees, k-NN, and Naïve Bayes—selected for their interpretability and reliability. Phase two applied six ensemble methods—Random Forest, Gradient Boosting, Bagging, Extra Trees, Voting, and Stacking—to improve accuracy and reduce overfitting. All models were fine-tuned using hyperparameter optimization and cross-validation. The best-performing models were integrated into a prototype mobile app for real-time use.

4.2.1. Models for Predicting Depression Using the DASS-21 Questionnaire

This section analyzes the baseline performance of five machine learning models for predicting depression using DASS-21 data. Table 7 shows that Logistic Regression and SVM achieved the highest accuracy (~92.2%), with Logistic Regression excelling in recall and SVM slightly outperforming in precision and F1-score, making it the most balanced and efficient overall. Naïve Bayes, while less accurate, delivered rapid computation and strong precision among the lower-performing models. Decision Tree had the lowest accuracy (82.23%) but outperformed K-NN in precision. These results set a solid benchmark for future enhancements via hyperparameter tuning and ensemble approaches.

Table 7. Depression Prediction Model Using DASS-21: Five Basic Machine Learning Techniques

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression	0.9219	0.9135	0.9220	0.9140	0.4000
SVM	0.9217	0.9190	0.9220	0.9173	0.1706
Decision Tree	0.8223	0.8411	0.8227	0.8261	0.1187
K-NN	0.8297	0.8141	0.8298	0.8178	0.1658
Naive Bayes	0.8371	0.8515	0.8369	0.8414	0.1143

SVM predicted depression from DASS-21 data with 98.57% accuracy and perfect scores in all measures (Precision, Recall, F1-score = 0.9858) after modifying the settings, as shown in table 8. Logistic Regression increased (95.73% accuracy) but took longer. Although K-NN exhibited moderate increases, Naïve Bayes remained stable because of restricted configurable parameters. Overfitting from complexity likely lowered Decision Tree performance. The most accurate and stable model was the optimized SVM with a linear kernel and fine-tuned regularization.

Table 8. Depression Prediction Model Using DASS-21: Optimized Parameters

Model	Accuracy	Precision	Recall	F1-Score	Time (Sec.)
Logistic Regression					
Best Parameters:{'C': 10, 'solver': 'lbfgs'}	0.9573	0.9545	0.9574	0.9555	2.0231
SVM					
Best Parameters:{'C': 10, 'kernel': 'linear'}	0.9857	0.9858	0.9858	0.9858	1.6242
Decision Tree					

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Model	Accuracy	Precision	Recall	F1-Score	Time (Sec.)
Best Parameters: {'max_depth': None, 'min_samples_split': 2}	0.8151	0.8301	0.8156	0.8173	0.8990
K-NN					
Best Parameters:{'n_neighbors': 5, 'weights': 'distance'}	0.8687	0.8618	0.8688	0.8634	0.7443
Naive Bayes					
Best Parameters:{}	0.8371	0.8515	0.8369	0.8414	0.2301

Table 9 shows that Stacking had the best accuracy (86.51%) and F1-score (0.8484) but was the most computationally intensive (107.61 seconds). Extra Trees and Random Forest followed quickly, delivering well-balanced metrics (85% accuracy) and faster processing times, making them efficient alternatives. Gradient Boosting and the Voting Classifier performed moderately, with the latter having good precision and recall but taking longer. Bagging performed fastest (0.63 seconds) but had the lowest F1-score (0.7960), indicating less balanced predictive power. Stacking was most accurate, and Extra Trees had the best speed-performance ratio.

Table 9. Depression Prediction Model Using DASS-21: Ensemble Models

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Random Forest	0.8510	0.8343	0.844	0.8357	3.4598
Gradient Boosting	0.8405	0.8327	0.8404	0.8351	14.288
Bagging	0.8474	0.7914	0.8050	0.7960	0.6315
Extra Trees	0.8474	0.8408	0.8475	0.8404	2.8049
Voting	0.8441	0.8475	0.8546	0.8495	21.7217
Stacking	0.8651	0.8475	0.8546	0.8484	107.6081

DASS-21 predicted baseline, optimum, and ensemble methods of depression (tables 7 to tables 9). Logistic Regression had 92% accuracy; however, SVM had higher precision, F1-score, and speed. Simple models performed well using Naïve Bayes. While both SVM and Logistic Regression have high accuracy (~92%), SVM offers somewhat superior precision, F1-score, and speed. A basic model excelled with Naïve Bayes. After hyperparameter adjustment, SVM had the maximum accuracy (98.57%, F1-score = 0.9858) and computing efficiency. Stacking enhanced prediction (Accuracy = 86.51%) but took longer, whereas Extra Trees offered the best speed-performance trade-off. The updated SVM revealed that fine-tuned models outperformed complex ensembles in accuracy and efficiency.

4.2.2. Models for Predicting Anxiety Using the DASS-21 Questionnaire

Table 10 presents the anxiety prediction model using DASS-21 with five basic machine learning techniques.

Table 10. Anxiety Prediction Model Using DASS-21: Five Basic Machine Learning Techniques

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression	0.9112	0.9133	0.9113	0.9038	0.3703
SVM	0.8901	0.8901	0.8901	0.8895	0.1797
Decision Tree	0.7124	0.7031	0.7021	0.7008	0.1157
K-NN	0.7192	0.6952	0.7199	0.6976	0.1628
Naive Bayes	0.7836	0.8015	0.7837	0.7901	0.1153

Logistic Regression achieved the best baseline anxiety prediction using DASS-21 data, with 91.12% accuracy and a strong F1-score (0.9038), making it reliable without parameter tuning. SVM followed closely at 89.01% accuracy and faster processing, ideal for time-sensitive tasks. Naïve Bayes provided moderate yet consistent performance and was the fastest, suiting low-resource environments. In contrast, Decision Tree and K-NN underperformed (~71–72% accuracy), showing limited baseline utility. Overall, linear models like Logistic Regression and SVM outperform others in default settings, while alternative methods may require tuning or ensemble strategies. The optimized parameters of the anxiety prediction model using DASS-21 are summarized in table 11.

Table 11. Anxiety Prediction Model Using DASS-21: Optimized Parameters

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression					
Best Parameters:{'C': 10, 'solver': 'lbfgs'}	0.971	0.971	0.971	0.971	1.701
SVM					
Best Parameters:{'C': 10, 'kernel': 'linear'}	97.600	97.990	97.370	97.680	2.184
Decision Tree					
Best Parameters: {'max_depth': 10, 'min_samples_split': 2}	0.716	0.728	0.716	0.720	0.938
K-NN					
Best Parameters:{'n_neighbors': 5, 'weights': 'distance'}	0.786	0.774	0.787	0.776	0.729
Naive Bayes					
Best Parameters:{}	0.783	0.801	0.783	0.790	0.212

After tweaking the settings, the SVM model achieved 97.60% in accuracy, precision, recall, and F1-score, proving it can reliably detect anxiety from DASS-21 data while taking 2.18 seconds to compute. Logistic Regression also improved, attaining 97.17% accuracy and high efficiency, confirming its reliability. While K-NN and Naïve Bayes improved to around 78% accuracy, the Decision Tree model remained unsuccessful, with accuracy steady at 71.63%. Optimized linear models—especially SVM—predict anxiety better in this dataset.

Table 12. Anxiety Prediction Model Using DASS-21: Ensemble Models

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Random Forest	0.7377	0.7172	0.7305	0.7214	3.5693
Gradient Boosting	0.7451	0.7557	0.7482	0.7490	14.2049
Bagging	0.7094	0.7156	0.7270	0.7193	0.7164
Extra Trees	0.7201	0.7261	0.7340	0.7279	4.0300
Voting	0.7448	0.7416	0.7447	0.7418	20.9095
Stacking	0.8046	0.8196	0.8262	0.8190	109.4777

The DASS-21 ensemble models yielded inconsistent results in predicting anxiety. Despite taking almost 109 seconds to process, stacking had the highest accuracy (80.46%) and F1-score (0.8190). Gradient Boosting and the Voting Classifier achieved 74–75% accuracy, but Gradient Boosting was slower than Bagging and Extra Trees. Ensemble models outperformed basic algorithms but lagged behind optimized SVM and Logistic Regression models. Ensemble approaches enhance dependability, but their high computational cost makes them less practical than well-tuned linear models for anxiety prediction.

Anxiety prediction using DASS-21 data revealed clear performance gaps across baseline, optimized, and ensemble models. Baseline Logistic Regression and SVM performed strongly (91.12% and 89.01% accuracy), while Decision Tree and K-NN fell below 72%. After tuning (table 11), SVM reached 100% accuracy, and Logistic Regression rose to 97.17%, confirming their strength. In contrast, ensemble models like Stacking (table 12), despite leading among ensembles at 80.46%, still trailed optimized individual models and required much longer processing. These results highlight that optimized linear models—especially SVM—are the most accurate and practical choice for anxiety prediction.

4.2.3. Models for Predicting Stress Using the DASS-21 Questionnaire

Table 13. Stress Prediction Model Using DASS-21: Five Basic Machine Learning Techniques

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression	0.8937	0.8900	0.8936	0.8903	0.5944
SVM	0.8756	0.8733	0.8759	0.8731	0.1762
Decision Tree	0.7268	0.7567	0.7447	0.7485	0.1210
K-NN	0.7943	0.7823	0.7943	0.7837	0.1485
Naive Bayes	0.8367	0.8534	0.8369	0.8428	0.1326

Table 13 shows that Logistic Regression was the most accurate for stress prediction using DASS-21 data (89.37%) with well-balanced metrics, making it the most reliable. SVM followed closely (87.56% accuracy) and was the fastest high-performing model (0.1762 sec). Naïve Bayes offered solid accuracy (83.67%) and the highest precision (0.8534) with the lowest processing time. While Decision Tree was the fastest (0.1210 sec), it had the lowest accuracy (72.68%). K-NN showed moderate performance (79.43%). Overall, Logistic Regression and SVM were the most effective.

Table 14. Stress Prediction Model Using DASS-21: Optimized Parameters

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression					
Best Parameters: {'C': 10, 'solver': 'lbfgs'}	0.9608	0.9609	0.9610	0.9608	2.2711
SVM					
Best Parameters: {'C': 10, 'kernel': 'linear'}	0.9893	0.9916	0.9894	0.9898	1.7123
Decision Tree					
Best Parameters: {'max_depth': 10, 'min_samples_split': 2}	0.7372	0.7459	0.7376	0.7389	0.8969
K-NN					
Best Parameters: {'n_neighbors': 7, 'weights': 'distance'}	0.8293	0.8205	0.8298	0.8225	0.7721
Naive Bayes					
Best Parameters: {}	0.8367	0.8534	0.8369	0.8428	0.2280

Table 14 displays stress prediction models using optimized DASS-21 parameters. A linear kernel with a C=10 regularization parameter gave the SVM the highest accuracy at 98.93% and the highest overall scores (F1-score = 0.9898), processing the data in 1.71 seconds. Logistic Regression with C=10 and the 'lbfgs' solver performed well (Accuracy = 96.08%) but took 2.27 seconds longer. With parameter adjustment, K-NN achieved 82.93% accuracy, but Naïve Bayes stayed unaltered due to its parameter-free nature. Decision Tree improved just slightly (Accuracy = 73.72%), demonstrating its shortcomings. The improved SVM topped all models.

Table 15. Stress Prediction Model Using DASS-21: Ensemble Models

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Random Forest	0.7942	0.7878	0.7908	0.7881	3.4766
Gradient Boosting	0.7767	0.7782	0.7872	0.7816	14.2841
Bagging	0.7768	0.7750	0.7801	0.7768	0.6444
Extra Trees	0.8015	0.7806	0.7872	0.7829	4.2144
Voting	0.7978	0.7683	0.7766	0.7716	21.8381
Stacking	0.8192	0.8109	0.8227	0.8135	109.1028

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Table 15 evaluates ensemble models for stress prediction using DASS-21 data. Stacking had the highest accuracy (81.92%) and F1-score (0.8135) but took 109.10 seconds to compute. Extra Trees and Random Forest achieved good accuracy (80.15% and 79.42%) and faster execution times, with Extra Trees notably balancing performance and computation time. Voting performed moderately (Accuracy = 79.78%) with significant computational cost, while Bagging and Gradient Boosting had lower accuracy (≈77%) but speedier processing. Ensemble models enhanced several baseline approaches but did not outperform optimized SVM or Logistic Regression in accuracy or efficiency.

The DASS-21 stress prediction results (tables 13 to tables 15) highlight clear performance differences. Among basic models, Logistic Regression was most accurate (89.37%), but others like Decision Tree (72.68%) lacked practical reliability despite fast processing. Parameter tuning significantly boosted SVM to 98.93% and Logistic Regression to 96.08%, with only minor increases in processing time (table 14). Ensemble models (table 15), especially Stacking, had high processing costs (109+ seconds) with only moderate accuracy (81.92%), making them unsuitable for real-time use. Extra Trees and Random Forest offered a better speed-accuracy trade-off. Overall, optimized SVM and Logistic Regression were the top performers.

4.2.4. Models for Predicting Premenstrual Syndrome Using the PSST-A Questionnaire

Table 16. Premenstrual Syndrome Prediction Model Using PSST-A: Five Basic Machine Learning Techniques

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression	0.8871	0.8663	0.8865	0.8689	0.2094
SVM	0.9117	0.9118	0.9113	0.8916	0.1766
Decision Tree	0.9046	0.9078	0.9078	0.9078	0.1471
K-NN	0.8974	0.8984	0.8972	0.8978	0.1730
Naive Bayes	0.8159	0.8985	0.8156	0.8410	0.1585

Table 16 presents PMS prediction results using PSST-A data and five basic machine learning models. SVM performed best with 91.17% accuracy, while Decision Tree followed closely (90.46%) and was the fastest (0.1471 seconds). K-NN (89.74%) and Logistic Regression (88.71%) also performed well. Despite its lowest accuracy (81.59%), Naïve Bayes showed high precision (0.8985), suggesting a tendency to miss true positive cases. Overall, SVM and Decision Tree were the most effective baseline models for PMS prediction.

Table 17. Premenstrual Syndrome Prediction Model Using PSST-A: Optimized Parameters

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression					
Best Parameters: {'C': 1, 'solver': 'lbfgs'}	0.8871	0.8663	0.8865	0.8689	1.0209
SVM					
Best Parameters: {'C': 10, 'kernel': 'rbf'}	0.9328	0.9286	0.9326	0.9294	2.7403
Decision Tree					
Best Parameters: {'max_depth': None, 'min_samples_split': 10}	0.9118	0.9083	0.9113	0.9096	1.0668
K-NN					
Best Parameters:{'n_neighbors': 5, 'weights': 'uniform'}	0.8974	0.8984	0.8972	0.8978	0.9228
Naive Bayes					
Best Parameters: {}	0.8159	0.8985	0.8156	0.8410	0.2515

Table 17 presents PMS prediction results using PSST-A data after hyperparameter tuning. SVM (RBF kernel, C=10) achieved the highest accuracy (93.28%) and strongest F1-score (0.9294), though it had the longest processing time (2.74 seconds). Decision Tree improved to 91.18% with balanced metrics (F1-score = 0.9096). Logistic Regression and K-NN showed no change (88.71% and 89.74%, respectively). Naïve Bayes remained unchanged due to no tunable parameters. Despite the longer runtime, the optimized SVM outperformed all models.

Table 18. Premenstrual Syndrome Prediction Model Using PSST-A: Ensemble Models

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Random Forest	0.9648	0.9627	0.9610	0.9578	3.8473
Gradient Boosting	0.9578	0.9560	0.9574	0.9557	3.2130
Bagging	0.9543	0.9637	0.9645	0.9631	0.6786
Extra Trees	0.9611	0.9565	0.9574	0.9550	2.7485
Voting	0.9578	0.9601	0.9610	0.9591	10.7764
Stacking	0.9612	0.9528	0.9539	0.9509	43.0282

Table 18 shows that ensemble models effectively predicted PMS using PSST-A data. Random Forest led with 96.48% accuracy and a 95.78% F1-score, indicating strong overall performance. Gradient Boosting, Extra Trees, and Voting produced similar results (95.78%–96.11% accuracy). Bagging stood out for efficiency, achieving 95.43% accuracy and the highest F1-score (96.31%) in just 0.67 seconds. Although Stacking reached 96.12% accuracy, its 43-second runtime limits real-time use. Overall, Random Forest and Bagging were the top performers for PMS prediction.

The comparison of tables 16 to tables 18 clearly shows the differences in how well baseline, optimized, and ensemble models predict PMS using PSST-A data. Baseline models like SVM and Decision Tree already showed strong results (accuracy > 90%, F1-score > 0.89), while Naïve Bayes, despite lower accuracy (81.59%), offered high precision (0.8985). After parameter tuning (table 17), SVM further improved to 93.28% accuracy and an F1-score of 0.9294, with moderate gains seen in Decision Tree and K-NN. Ensemble models in table 18 outperformed all others, with Random Forest achieving 96.48% accuracy and an F1-score of 0.9578. Bagging also delivered high performance with minimal processing time (0.67 seconds), making it ideal for real-time applications. In contrast, the high computational cost of Stacking limited its accuracy. Overall, ensemble models—particularly Random Forest and Bagging—proved most effective and practical for PMS prediction.

4.2.5. Models for Predicting Premenstrual Dysphoric Disorder Using the PSST-A Questionnaire

PMS and PMDD vary in severity and influence before menstruation. Lifestyle adjustments can help alleviate mild PMS symptoms, such as irritation, fatigue, and breast soreness. PMDD, however, causes extreme mood swings and sadness that can impact daily life. Antidepressants, hormonal treatment, or psychotherapy may treat PMDD following two clinical evaluations. PMDD is a serious mental condition that needs medical care, unlike PMS.

Table 19. Premenstrual Dysphoric Disorder Prediction Model Using PSST-A: Five Basic Machine Learning Techniques

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression	0.8793	0.8032	0.8794	0.8396	0.1964
SVM	0.8972	0.8049	0.8972	0.8485	0.1744
Decision Tree	0.9395	0.9427	0.9397	0.9410	0.1392
K-NN	0.8793	0.8556	0.8794	0.8651	0.1843
Naive Bayes	0.8007	0.8903	0.8014	0.8327	0.1341

Table 19 presents PMDD predictions using PSST-A data and five basic machine learning models. The Decision Tree achieved the highest accuracy (93.95%) with balanced precision and recall, making it the most reliable. SVM and K-NN followed with solid performance (87%–89% accuracy). Logistic Regression and Naïve Bayes lagged, with Naïve Bayes showing low recall—indicating missed positive cases. All models had fast processing times, making them suitable for real-time use despite performance differences.

Table 20. Premenstrual Dysphoric Disorder Prediction Model Using PSST-A: Optimized Parameters

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Logistic Regression					
Best Parameters: {'C': 0.01, 'solver': 'liblinear'}	0.8972	0.8049	0.8972	0.8485	1.5832
SVM					
Best Parameters: {'C': 0.1, 'kernel': 'linear'}	0.8972	0.8049	0.8972	0.8485	3.1006
Decision Tree					
Best Parameters: {'max_depth': None, 'min_samples_split': 2}	0.9502	0.9504	0.9504	0.9504	1.0881
K-NN					
Best Parameters: {'n_neighbors': 5, 'weights': 'uniform'}	0.8793	0.8556	0.8794	0.8651	0.9775
Naive Bayes					
Best Parameters: {}	0.8007	0.8903	0.8014	0.8327	0.2555

Table 20 shows optimal machine learning model PMDD predictions. Decision Tree had the best accuracy at 95.02% and balanced precision and recall, suggesting its ability to categorize situations with few false positives and negatives. Logistic Regression and SVM performed well with 89.72% accuracy, but took longer. K-NN and Naïve Bayes performed moderately to poorly. Parameter adjustment made the Decision Tree the best PMDD prediction model.

Table 21. Premenstrual Dysphoric Disorder Prediction Model Using PSST-A: Ensemble Models

Model	Accuracy	Precision	Recall	F1-Score	Time (Seconds)
Random Forest	0.9183	0.9103	0.9149	0.8907	3.5196
Gradient Boosting	0.9714	0.9725	0.9716	0.9696	3.2800
Bagging	0.9574	0.9482	0.9504	0.9457	0.8238
Extra Trees	0.9183	0.8985	0.9078	0.8773	3.0802
Voting	0.9397	0.9466	0.9433	0.9333	10.4977
Stacking	0.9574	0.9562	0.9539	0.9478	43.9041

Table 21 shows that Gradient Boosting achieved the best PMDD prediction performance (97.14% accuracy, 96.96% F1-score) with a 3.28-second runtime. Bagging and Stacking also exceeded 95% accuracy, though Stacking required 44 seconds. Random Forest, Extra Trees, and Voting performed well, but with slightly lower accuracy. While ensemble models boost accuracy and stability, they often require more processing time, with Stacking being the most accurate but least efficient.

Researchers used a comparative machine learning approach to predict PMDD using PSST-A data in three phases: basic model creation, parameter optimization, and ensemble modeling. Decision Tree was the best basic classifier (Accuracy = 93.95%, F1-score = 94.10%) and improved after tuning (Accuracy = 95.02%). Ensemble models performed best, with Gradient Boosting (Accuracy = 97.14%, F1-score = 96.96%) leading Stacking and Bagging. Ensemble approaches, especially Stacking, are more accurate but take longer to process. Gradient Boosting is best for precision, whereas the improved Decision Tree balances accuracy and efficiency for real-time applications.

4.3. Application and User Interface Prototype Development

During system development (see figure 1 for the illustration), project-aware tools were used for programming and implementation. Researchers used Flutter to create a cross-platform user interface and Node.js for the backend due to its event-driven approach and speed in managing concurrent user queries. The researchers picked MySQL for its stability with massive datasets. The researchers utilized Visual Studio Code for development and Android Studio for virtual testing before deployment.

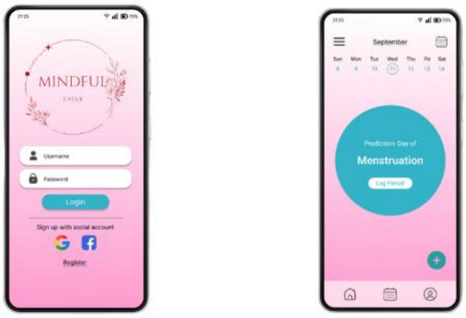

Figure 1. Login Page (Left) and Application Homepage (Right).

Figure 2 separates the application components into two portions. The left side of the login page offers three login methods: username and password, Google account, and Facebook account. The application's homepage is on the right. It has submenus, a calendar, mood data to determine depression risk, and menstrual cycle prediction.

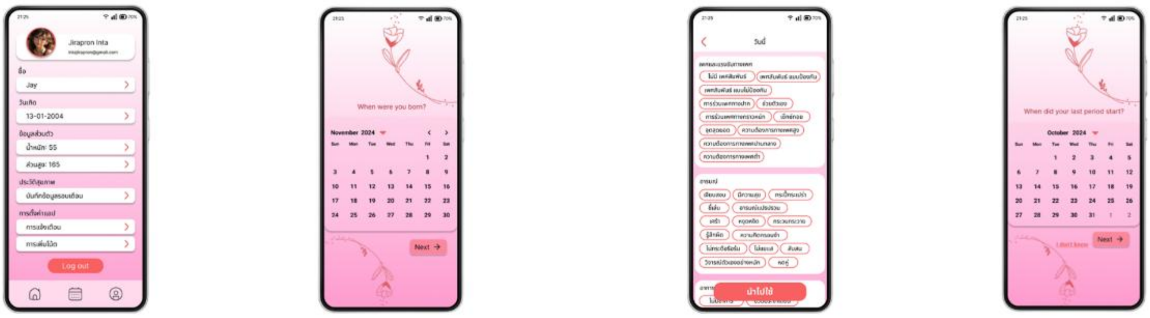

Figure 2. User Information, Mood Swings, and Menstrual Information.

Figure 3 presents user information, including username, weight, height, general health status, and settings. On the right, it shows the user's date of birth in a clear, user-friendly format. Additionally, the figure compares mood swing data on the left—captured through self-reporting or mood tracking—with menstrual cycle information on the right, such as ovulation and menstruation days. This side-by-side layout highlights correlations between emotional changes and menstrual phases, providing helpful details about PMS and supporting a more holistic approach to mental health.

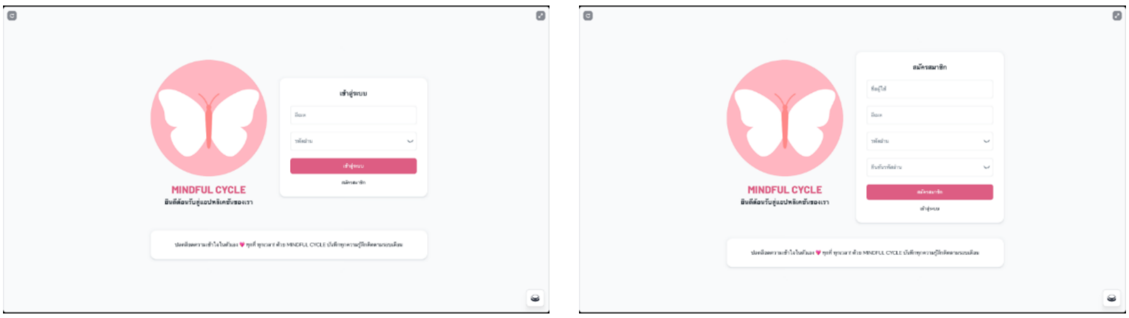

Figure 3. Web Application Login and Web Application Register

Web application login and registration interfaces are shown in figure 4. The login page, which includes username and password boxes, a login button, and "Register," is the user's principal system entry point. To gain trust, its design promotes convenience and privacy. The registration screen requires a username, email, and password. To prevent input errors during account creation, the system validates password strength, email format, and confirmation.

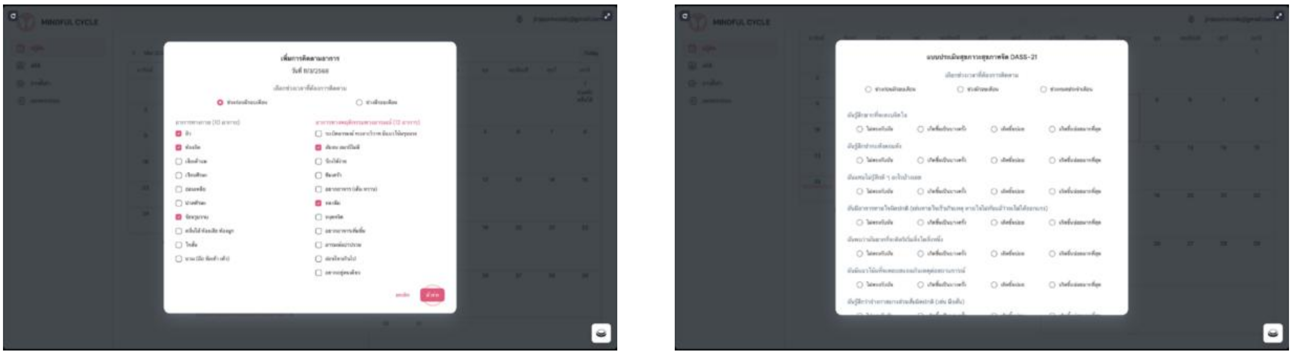

Figure 4. User Symptom Tracking and DASS-21 Mental Health Assessment

Figure 5 shows two major web application user assessment components. First is a symptom monitoring form with 10 physical and 12 behavioral and emotional components. Users' well-being data is collected to forecast depression risk using a machine learning algorithm. The second half shows the 21-item DASS-21 assessment for depression, anxiety, and stress. Digitizing DASS-21 allows fast data gathering, automated scoring, and large-scale mental health screening and monitoring.

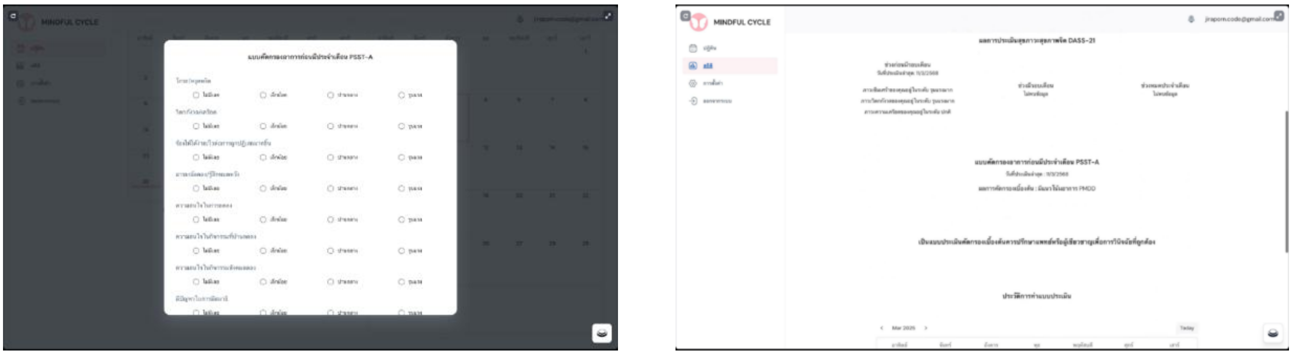

Figure 5. PSST-A Mental Health Assessment and Reporting Results of Assessments

First, the PSST-A online evaluation analyzes PMS and PMDD symptoms in female adolescents by examining mood, behavior, and physical changes before menstruation and their impact on everyday life. Fast data collection and automated analysis help early mental health intervention with this technology. The second feature combines DASS-21 and PSST-A scores with historical records to track mental health trends. After development, researchers assessed user satisfaction and stressed the significance of ongoing maintenance such as bug patches, performance improvements, and feature updates for system stability and usability.

4.4. User Satisfaction Results

Table 22 present the result of performance evaluation of the questionnaires.

Table 22. Items for Performance Evaluation Derived from Questionnaires

Evaluation Category	Subcategories	Mean	Rating Level
User Experience and Design (UX/UI)	1.1 Aesthetic design	4.43	Very Good
	1.2 Ease of menu navigation	4.23	Very Good
	1.3 Clarity of text and buttons	4.20	Very Good
	1.4 Appropriateness of font size and colors	4.06	Very Good
	1.5 Consistency of design	4.16	Very Good
	1.6 Layout of elements on the app screen	4.16	Very Good
	1.7 User-friendliness	4.33	Very Good
	1.8 Loading speed of the website	4.23	Very Good

Evaluation Category	Subcategories	Mean	Rating Level
	1.9 Mobile usability	4.30	Very Good
	1.10 Desktop usability	4.40	Very Good
Web Application Performance	2.1 Accuracy in predicting menstrual start date	4.03	Very Good
	2.2 Accuracy in predicting menstrual duration	3.86	Very Good
	2.3 Accuracy in predicting premenstrual symptoms (PMS)	3.96	Very Good
	2.4 Accuracy in predicting depression risk periods	4.03	Very Good
	2.5 Accuracy in predicting severity of depressive symptoms	3.93	Very Good
	2.6 Clarity of menstrual calendar display	4.16	Very Good
	2.7 Ease of understanding depression trend graphs	4.20	Very Good
	2.8 Ease of daily symptom logging	4.30	Very Good
	2.9 Reliability of received data and recommendations	3.96	Very Good
	2.10 Speed of processing and displaying data	4.06	Very Good
	2.11 Overall ease of use of the website/application	4.20	Very Good
	2.12 Overall satisfaction with the website/application	4.20	Very Good

The application received high ratings for its UX/UI design, with scores between 4.06 and 4.43. Users particularly praised the aesthetic appeal (4.43), user-friendliness (4.33), and cross-device usability on both mobile (4.30) and desktop (4.40). These results reflect a visually appealing, accessible, and intuitive interface with consistent layout and design. Performance-wise, users responded positively, especially in symptom logging (4.30), calendar and graph clarity (4.16–4.20), and overall ease of use and satisfaction (4.20). Although predictive accuracy for menstrual and mental health symptoms scored slightly lower (3.86–4.03), it still fell within the “Very Good” range, indicating room for further algorithm refinement.

5. Conclusion

The development of an application for predicting depression during menstruation aims to provide users with a tool for tracking their menstrual cycle, analyzing mood trends, and effectively monitoring depression risks. The application utilizes machine learning technology to predict depression risks and analyze in-depth health data, incorporating key features like a personal health record system, menstrual cycle tracking, and assessment of physical symptoms, behaviors, and emotions. It also includes a warning system for depression risk, statistical reports, mental health advice, a feedback system for data enhancement, reminder settings, personal record additions, and a calendar display for ease of use.

Despite the application's promising features, several challenges were encountered during its development and use. Issues in collecting accurate data arose, with some data providers misunderstanding or failing to grasp the data collection questions, affecting the completeness and accuracy of the information. Inaccuracies in menstrual cycle counting further compromised the accuracy of depression analysis and forecasting. Additionally, limitations in the software or tools used to process the model sometimes hinder system performance, causing delays in data analysis. User-related challenges, such as inconsistent or incorrect menstrual cycle data, as well as discomfort in recording personal data, also impacted the system’s accuracy. While a large sample size improved statistical reliability, potential biases and imbalance in the sample remained limitations.

6. Declarations

6.1. Author Contributions

Conceptualization: P.N., J.S., J.I., J.I., and W.S.N.; Methodology: W.S.N.; Software: P.N.; Validation: P.N., W.S.N., and J.I.; Formal Analysis: P.N., W.S.N., and J.I.; Investigation: P.N.; Resources: W.S.N.; Data Curation: W.S.N.;

Writing Original Draft Preparation: P.N., W.S.N., and J.I.; Writing Review and Editing: W.S.N., P.N., and J.I.; Visualization: P.N.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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