AFTER PREDICTION: PREDICTIVE ANALYTICS FOR ACHIEVING A STRESS-FREE STATE.

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Abstract

Stress is a widespread issue affecting mental and physical health, contributing to anxiety, depression, cardiovascular diseases, and weakened immunity. Traditional stress management methods, such as yoga, meditation, and Ayurveda, have been practiced for centuries but often lack personalization and real-time tracking. In contrast, modern ML-driven solutions provide data insights but fail to integrate holistic healing. This disconnects results in fragmented, ineffective stress management strategies. To address this gap, *AyurAura* integrates Ayurvedic principles with ML to create a dynamic, user-centric stress management system. The system visualizes progress, predicts recovery timelines, and provides personalized feedback. Predictive algorithms estimate the time needed to achieve a stress-free state based on adherence to therapeutic activities and lifestyle modifications. Key features include mood and energy tracking, progress analytics, and ML-driven recommendations. AyurAura's MLmodels analyze user data from questionnaires, eye-blinking rates, breathing patterns, music therapy engagement, and daily emotional tracking to refine stress predictions. A user-friendly interface enables seamless data reporting and visualization. By combining holistic healing with ML-driven insights, AyurAura offers an adaptive stress management approach. This study presents the conceptual framework, design, and methodology of AyurAura, aiming to revolutionize stress management through personalized, data-driven strategies that empower users to regain mental well-being.

Keywords: Stress Management, Ayurveda, Artificial Intelligence, Machine Learning, Personalized Feedback.

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List Of Abbreviations

Abbreviation	Description
ML	Machine Learning
TCM	Traditional Chinese Medicine
CBT	Cognitive-Behavioral Therapy
SSRIs	selective serotonin reuptake inhibitors
DEQ	Discrete Emotions Questionnaire
KNN	K-Nearest Neighbors
MAE	Mean Absolute Error
R^2	R-squared
SMOTE	Synthetic Minority Over-sampling Technique
API	Application Programming Interface

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1.Introduction

1.1.Background

In the contemporary world, stress has emerged as a prevalent concern, impacting individuals from all walks of life. The demands of modern living, including balancing professional responsibilities, maintaining personal relationships, and navigating societal expectations, have significantly contributed to heightened stress levels. As a result, individuals often experience a decline in mental and physical well-being, which can lead to long-term health complications if left unmanaged [1]. Chronic stress has been linked to various medical conditions, including cardiovascular diseases, high blood pressure, weakened immune function, anxiety disorders, and depression. Additionally, prolonged stress can impair cognitive function, disrupt sleep patterns, and reduce overall productivity, further exacerbating the negative consequences on an individual's quality of life. Addressing this pressing issue requires innovative solutions that offer personalized, effective, and accessible stress management strategies.

Throughout history, different cultures have recognized the detrimental effects of stress and developed unique methods to manage it. Traditional healing practices such as Ayurveda, TCM, and indigenous therapeutic approaches emphasize holistic methods that integrate physical, mental, and emotional well-being. Ayurveda, an ancient Indian medical system, advocates for a balanced lifestyle through herbal treatments, dietary modifications, yoga, meditation, and personalized daily routines tailored to an individual's unique constitution [2] Similarly, TCM incorporates acupuncture, t MLchi, and herbal medicine to restore energy balance and reduce stress-related symptoms. These ancient systems focus on long-term well-being by addressing the root causes of stress rather than merely alleviating symptoms.

In contrast, modern stress management solutions have largely centered around pharmaceutical interventions and CBT. While these methods are scientifically validated and effective for many individuals, they may not always be accessible, affordable, or suitable for long-term self-management. Medications for stress and anxiety, such as SSRIs and benzodiazepines, can provide relief but often come with side effects and the risk of dependency. Likewise, psychotherapy and CBT offer structured approaches to stress management, but they may require consistent access to mental health professionals, which can be a challenge for individuals in underserved communities or those with time constraints.

Given these limitations, a growing need exists for an integrated approach that combines the strengths of both traditional wisdom and modern technology. Leveraging advancements in ML, stress management solutions can become more personalized, adaptive, and accessible. ML-driven applications can analyze user data, track behavioral patterns, and provide tailored recommendations that align with holistic healing practices. By merging traditional stress-relief techniques with data-driven insights, it is possible to develop a comprehensive system that not only alleviates stress but also enhances overall well-being through continuous monitoring and personalized interventions.

This paper explores the need for a synergistic approach that bridges the gap between traditional and contemporary stress management techniques. By integrating the wisdom of Ayurveda with the precision of ML-powered analytics, the proposed solution aims to revolutionize how stress is understood and managed in the modern world.

With advancements in ML, digital health solutions have become increasingly prevalent, offering users greater insight into their overall well-being. Wearable devices, mobile applications, and online therapy platforms have revolutionized healthcare by providing real-time monitoring and personalized recommendations for physical health parameters such as heart rate, sleep patterns, and activity levels [3]. These technologies empower individuals to take charge of their health, promoting proactive wellness management. However, despite these advancements, many existing digital health solutions focus primarily on physical activity metrics, often overlooking the critical aspects of mental and emotional well-being. As a result, stress management remains fragmented, with users unable to access a fully integrated solution that considers their overall health comprehensively.

Our research proposes the development of a dynamic system that integrates Ayurvedic principles with ML technologies to offer a holistic approach to stress management. This system is designed to visualize changes in users' daily routines, track progress over time, and estimate the time required to achieve a stress-free state based on adherence to a recommended activity plan [2] [4] Unlike conventional applications that provide generic stress-relief tips, this system employs predictive modeling to generate personalized feedback, ensuring that recommendations are tailored to individual needs and behavioral patterns. By incorporating both ancient holistic healing methods and modern technological advancements, the system aims to create a well-rounded stress management experience that adapts to users' evolving conditions.

A key feature of the proposed system is an intuitive, user-friendly interface that facilitates seamless interaction and engagement. Users will be prompted to report their daily mood, energy levels, and adherence to recommended activities using various interactive tools such as sliders, emojis, and text inputs [5]. These tools provide a simple yet effective way for users to communicate their emotional state and track their progress without feeling overwhelmed by complex data entry processes. To promote consistent engagement, the system will implement a notification and reminder mechanism, ensuring users complete daily check-ins and maintain an accurate record of their well-being [6] This consistency in data collection is crucial for generating meaningful insights and refining stress predictions over time.

Furthermore, the system's ML-driven analytics will process the collected data to identify trends and patterns in user behavior. By analyzing fluctuations in reported mood, energy levels, and activity adherence, the system will generate insights that help users understand the factors influencing their stress levels. These insights will be presented through visual progress analytics, allowing users to recognize improvements, setbacks, and necessary adjustments to their stress management routines. Additionally, by continuously learning from user data, the MLalgorithms will refine recommendations, enhancing their effectiveness and ensuring they remain relevant to the user's evolving needs.

By integrating ML-powered data analysis with Ayurvedic wisdom, this system aims to bridge the gap between traditional healing practices and modern stress management solutions. Unlike conventional methods that operate in isolation, the proposed system leverages the strengths of both domains, offering a personalized and adaptive approach to stress relief. Through predictive modeling, real-time tracking, and interactive user engagement, this research presents a transformative solution that empowers individuals to proactively manage their stress in a holistic and scientifically informed manner.

To enhance user engagement, predictive algorithms will be employed to estimate the timeline for achieving a stress-free state based on adherence to the recommended activity plan. These algorithms will analyze user behavior patterns, including mood fluctuations, energy levels, and completion of prescribed stress-relief activities, to provide realistic projections of recovery time. By leveraging historical data and machine learning models, the system will dynamically adjust predictions, offering users a clearer understanding of their progress and expected improvements. Personalized insights will help individuals set achievable wellness goals, motivating them to maintain consistency in their stress management routines.

In addition to predictive analytics, the system introduces an innovative reward mechanism to further encourage active participation. Users will receive Elemental Tokens representing the five Ayurvedic elements—Earth, Water, Fire, Air, and Ether—which are fundamental to maintaining balance in Ayurveda. These tokens will serve as a form of in-app currency that can be earned through consistent engagement, such as completing daily check-ins, adhering to recommended activities, and achieving stress-reduction milestones. Users can then redeem these tokens for exclusive in-app content, including guided Ayurvedic practices, meditation exercises, [7] breathing techniques, and personalized wellness tips tailored to their specific needs This gamification strategy not only fosters motivation but also reinforces the connection between traditional healing principles and modern technological solutions.

By integrating elements of Ayurveda into a digital platform, this project effectively bridges ancient wisdom with contemporary ML-driven healthcare. Unlike conventional wellness applications that rely solely on clinical data and generalized recommendations, this system incorporates a holistic framework that recognizes the interplay between physical, mental, and emotional health. Ayurveda emphasizes individualized treatment plans based on unique body constitutions and by aligning this philosophy with ML-based personalization, the proposed solution offers an adaptive and user-centric approach to stress management.

Through data-driven insights and interactive engagement features, this system empowers users to take control of their mental health and well-being. Rather than providing generic stress management tips, it delivers tailored interventions that evolve in response to the user's lifestyle choices and physiological changes. By tracking progress over time and offering tangible rewards for commitment, the platform cultivates sustainable stress-relief habits, ultimately guiding individuals toward a balanced, harmonious, and stress-free life.

1.2.Literature Review

The growing prevalence of stress in modern society has led to the development of various stress management solutions, ranging from traditional healing practices to digital interventions. However, many of these solutions lack an integrated approach that effectively combines time-tested holistic methods with modern technological advancements. Traditional systems such as Ayurveda, an ancient Indian medical practice, emphasize holistic well-being through herbal treatments, meditation, controlled breathing exercises, and personalized lifestyle adjustments [2] These methods focus on achieving balance in the body and mind, offering long-term stress management solutions rather than quick, temporary relief. Studies indicate that Ayurvedic therapies, including adaptogenic herbs, yoga, and Pranayama (breathing techniques), can effectively reduce stress levels and improve overall well-being. However, despite their potential, these practices often remain inaccessible, unstructured, or difficult to personalize for modern users who may lack the necessary guidance to implement them effectively in daily life [8]

On the other hand, advancements in ML technologies have enabled the creation of digital stress management tools that analyze user data, detect patterns in behavior, and offer personalized recommendations for mental well-being [9]. These ML-driven solutions leverage physiological tracking, behavioral analytics, and real-time feedback to provide users with actionable insights. While promising, many of these technological solutions lack the depth and personalization that holistic health approaches like Ayurveda inherently offer. Most ML-based applications primarily focus on tracking physical activity, heart rate variability, and general health metrics without providing a truly comprehensive view of mental and emotional well-being

[10]. Consequently, these applications may overlook critical factors influencing stress, such as personal habits, emotional resilience, and lifestyle preferences.

A key component in stress assessment is self-reporting, which allows individuals to document their emotional and physical states over time. Self-reporting tools such as the DEQ have proven effective in capturing real-time emotional states, making them a valuable resource for understanding stress patterns [11]. By analyzing emotions like anxiety, frustration, or relaxation at different points in the day, these tools provide meaningful insights into an individual's mental health. However, despite their effectiveness, existing self-reporting tools have significant limitations—they often lack predictive capabilities, rely heavily on user compliance, and fail to incorporate engagement mechanisms that encourage long-term adherence to stress management routines. Without personalized engagement features, users may lose interest in consistently tracking their emotional states, reducing the overall impact of these tools on stress management.

By integrating Ayurvedic principles with ML-driven insights, our proposed system seeks to fill the critical gaps in existing stress management solutions by offering a holistic, personalized, and data-driven approach. Unlike conventional digital wellness applications that primarily focus on either physical health tracking or generalized stress-relief techniques, this system will incorporate individualized recommendations based on a user's unique stress profile, lifestyle, and adherence to prescribed activities. The fusion of ancient Ayurvedic wisdom with modern ML capabilities ensures that users receive a well-rounded approach to stress management that addresses not only immediate symptoms but also long-term well-being.

The system will actively track users' mental and physical well-being through multiple input sources, including self-reported emotional states, behavioral patterns, and physiological indicators such as eye-blinking rate. By leveraging machine learning models, the system will analyze trends in a user's emotional fluctuations, activity engagement, and stress triggers to refine personalized wellness plans.

A key differentiating feature of this system is its ability to visualize progress in an intuitive and interactive manner. Users will have access to comprehensive dashboards displaying their stress levels over time, insights into behavioral patterns, and predictions regarding their expected recovery timelines. By providing real-time feedback and data-driven projections, the platform helps individuals understand the effectiveness of their stress-relief activities and encourages them to stay committed to their wellness journey. The system will also utilize predictive analytics to estimate stress recovery timelines, offering users a realistic expectation of how long it will take to achieve a stress-free state based on their adherence to recommended therapeutic activities, mindfulness exercises, and lifestyle adjustments.

To further enhance user engagement and motivation, the platform will incorporate gamification and reward-based mechanisms. Users will earn Elemental Tokens representing the five fundamental Ayurvedic elements—Earth, Water, Fire, Air, and Ether—which will serve as a form of in-app currency. These tokens can be accumulated through consistent participation, such as completing daily check-ins, following recommended activities, and achieving stress reduction milestones. Users will then have the opportunity to redeem these tokens for exclusive in-app content, including more mandala arts, music tracks, and personalized wellness recommendations. By incorporating interactive engagement elements, the system ensures long-term user retention, motivation, and adherence to stress management strategies.

By bridging the gap between traditional holistic healing and modern technology, this ML-integrated Ayurvedic system represents a revolutionary advancement in stress management. Through personalized recommendations, real-time progress visualization, predictive analytics, and engaging reward systems, the platform empowers users to take proactive control of their mental, emotional, and physical well-being. This innovative approach not only enhances long-term stress resilience but also promotes a balanced and sustainable lifestyle, making it a comprehensive solution for stress relief in today's fast-paced world..

1.3.Research Gap

Despite extensive research on stress management, critical gaps remain unaddressed, limiting the effectiveness of existing interventions. Most studies focus on either Ayurvedic practices or ML-driven interventions in isolation, failing to integrate these approaches into a cohesive, data-driven, and holistic system [8]. While

Ayurveda provides a rich framework for personalized healing through herbal treatments, yoga, meditation, and lifestyle modifications, it lacks real-time tracking, adaptive feedback, and engagement mechanisms that encourage long-term adherence. On the other hand, ML-based stress management solutions leverage machine learning models, physiological tracking, and predictive analytics to offer tailored insights, but they often overlook the cultural and holistic dimensions of stress relief [7] [9].

Another major gap in current solutions is the lack of personalized stress recovery projections. Many stress management applications provide generalized recommendations without considering individual differences in lifestyle, adherence levels, and emotional resilience. Without a system that estimates the specific timeline for achieving a stress-free state based on user behavior, individuals may struggle to gauge their progress and lose motivation. While some applications incorporate basic mood tracking and ML-powered insights, they often lack continuous feedback loops and real-time progress visualization, making it difficult for users to stay engaged and track their improvement effectively [12]

Moreover, current ML-based stress management tools rarely incorporate engagement mechanisms designed to sustain long-term adherence. Research suggests that gamification elements, such as reward-based progress tracking, can significantly enhance motivation and user retention in wellness applications [12] However, most existing platforms fail to integrate meaningful incentive structures, such as personalized rewards, milestone achievements, and interactive engagement features. Without these mechanisms, users may struggle to maintain consistency in their stress reduction activities, leading to lower success rates in achieving lasting emotional well-being.

To address these limitations, our research introduces a novel stress management system that merges the wisdom of Ayurveda with the predictive capabilities of ML. This integrated approach will allow users to:

- Dynamically track their stress levels through a combination of self-reported emotional states and activity engagement metrics.
- Receive real-time personalized feedback based on their adherence to recommended Ayurvedic practices and behavioral modifications.

- Visualize their progress through an interactive dashboard, offering stress trend analysis and predictive recovery timelines.

Additionally, to enhance long-term engagement and adherence, the system will incorporate gamification and reward-based features, including:

- Elemental Tokens, inspired by the five fundamental Ayurvedic elements—Earth, Water, Fire, Air, and Ether—earned through consistent participation in wellness activities.
- Milestone-based rewards, where users unlock guided meditation sessions, personalized wellness tips, and -generated stress-relief exercises.
- A motivational notification system that offers personalized encouragement based on the user's progress and stress-reduction achievements.

By bridging ancient holistic practices with cutting-edge ML-driven insights, our system stands apart from existing interventions by providing a personalized, culturally relevant, and scientifically validated approach to stress management. This integrated framework empowers individuals to take proactive control over their mental health, ensuring a sustainable, engaging, and effective path to stress reduction and overall well-being.

1.4.Research Problem

The increasing prevalence of stress necessitates comprehensive, adaptive, and personalized management solutions that cater to individual differences in stress triggers, coping mechanisms, and recovery patterns. Current approaches—whether Ayurvedic, technological, or behavioral—offer valuable insights but are often implemented in isolation, lacking a unified framework that effectively combines traditional wisdom with modern advancements [1] [2]. As a result, existing solutions fail to provide a seamless, engaging, and data-driven approach that supports users throughout their stress management journey.

Most stress management tools suffer from fragmentation, as they focus on either progress tracking, predictive analytics, or engagement mechanisms, rather than integrating these crucial elements into a single accessible platform. For instance, while creative therapies and Ayurvedic practices are widely recognized for their stress-relieving benefits, they are rarely incorporated into ML-driven health solutions that rely primarily on data analytics and physiological tracking [3] Similarly, ML-based mood monitoring tools, which leverage natural language processing and sentiment analysis, provide valuable insights into emotional fluctuations but often lack culturally relevant stress management techniques, such as Ayurveda's dosha-based lifestyle recommendations, herbal therapies, and mind-body balancing exercises. Without an integrated approach, these systems fail to cater to the diverse needs of users, limiting their ability to achieve long-term stress reduction and emotional well-being.

The research problem, therefore, is to develop an innovative stress management system that synthesizes Ayurvedic principles with ML technologies to create a personalized, intelligent, and holistic solution. This system will offer dynamic stress tracking by:

- Monitoring daily mood changes through self-reporting tools and activity completion rates.
- Visualizing stress recovery progress via interactive dashboards that display stress level fluctuations, emotional patterns, and engagement metrics.
- Projecting personalized recovery timelines based on ML-driven predictive analytics that adapt recommendations in real-time.

To enhance user adherence and motivation, the system will integrate engagement strategies, including gamification features, adaptive feedback loops, and Ayurvedic-inspired rewards. For example:

- Users will earn Elemental Tokens, representing Ayurveda's five elements (Earth, Water, Fire, Air, and Ether), which can be exchanged for stress-relief exercises, and customized wellness tips.
- The platform will provide milestone-based encouragement, where users unlock exclusive stress management content as they achieve progress goals.
- A notification system will offer real-time feedback and reminders tailored to individual stress patterns and activity completion rates.

By addressing these gaps in stress management, the proposed solution will provide a holistic and scientifically validated approach that acknowledges the multifaceted nature of stress. This research aims to empower individuals with a structured yet flexible framework that combines traditional healing methods with ML-driven intelligence, ultimately improving mental well-being and fostering sustainable stress reduction.

1.5.Research Objectives

The primary aim of this research is to develop a holistic and adaptive stress management system that integrates Ayurvedic therapies with advanced ML technologies. The system will focus on predicting stress levels, tracking daily emotional and activity changes, and projecting a recovery timeline, thereby offering personalized stress management solutions.

1.5.1.General Objective

To develop an innovative and dynamic system that combines traditional Ayurvedic approaches with state-of-the-art ML techniques to provide a comprehensive and personalized stress management solution. This system will track daily mood variations, visualize progress, and estimate the recovery period needed to attain a stress-free state.

1.5.2.Specific Objectives

1) Design a User-Friendly Interface:
    - Create an intuitive interface that allows users to record their daily mood and energy levels using interactive sliders, emojis, and brief text inputs.
    - Ensure ease of use and seamless navigation to encourage consistent user engagement.

2) Develop a Consistent Notification System:
    - Implement a non-intrusive notification system that gently reminds users to complete daily check-ins and record their emotional states.
    - Enhance data accuracy through consistent user engagement. [13]
3) Incorporate Data Analytics for Progress Tracking:
    - Enable users to customize their progress visualization by selecting specific time ranges or metrics such as mood versus energy levels.

- Present data in an easily interpretable format to foster self-awareness and motivation.

4) Implement Predictive Algorithms for Timeline Projection:
   - Develop machine learning algorithms to predict the estimated time required to achieve a stress-free state based on users' adherence to recommended activities and mood progression.
   - Visualize the recovery timeline to enhance user motivation and goal setting.

5) Create a Reward and Recognition System:
   - Introduce a system of rewards or recognition for achieving key milestones, leveraging Ayurvedic elements (Earth, Water, Fire, Air, Ether) to symbolize progress.
   - Encourage consistent participation through motivational incentives and rewards.

6) Provide Personalized Feedback and Adjustments:
   - Generate regular progress reports that summarize achievements, current status, and areas needing improvement.
   - Offer personalized recommendations and insights based on data analytics to help users maintain consistent progress.

2.Methodology

This study followed an experimental and data-driven approach to develop an advanced stress management system integrating Ayurvedic therapeutic concepts with machine learning techniques. The primary objective was to design an adaptive model that predicts stress recovery timelines based on user-reported emotional states and activity completion rates as shown in Fig.1. By leveraging data-driven insights and predictive analytics, the system was built to dynamically adjust its recommendations based on user engagement, ensuring a personalized and effective stress management experience. The research methodology involved multiple phases, including data collection, preprocessing, feature engineering, model development, training, evaluation, deployment, and validation, to ensure accuracy, reliability, and robustness in predictions.

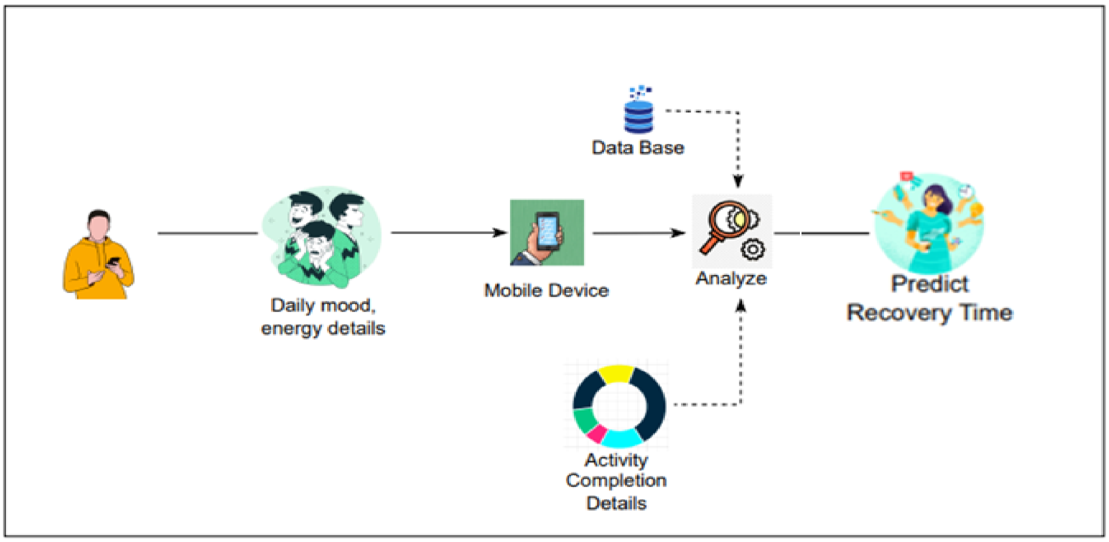

Fig. 1.Flow of Prediction of Recovery Time to Stress-Free State

2.1. Data Collection and Dataset

The dataset used for this study was collected through a combination of manually recorded data and digital self-reporting tools, ensuring a comprehensive and structured approach to analyzing stress patterns. In an effort to capture meaningful insights, we closely monitored a diverse group of 200 individuals, all aged 18 and above, over a continuous 14-day period. Participants were required to log their emotional states daily, specifically tracking levels of happiness, calmness, and stress. Additionally, they recorded their engagement in two key therapeutic activities—

Mandala art coloring and music therapy. By structuring data collection in this manner, we generated a rich dataset containing 2,800 individual data points, capturing fluctuations in stress levels as well as adherence to creative therapeutic practices over time.

To enhance the accuracy and reliability of our dataset, we implemented a dual data collection method that incorporated both self-reported and observational data. Participants primarily recorded their emotional responses and activity completion details through a structured Google Form, which facilitated standardized data entry and reduced inconsistencies. At the same time, we complemented this self-reported data with direct monitoring of participants' engagement in stress-management activities. To achieve this, we used applications similar to those designed for Mandala art coloring and music track listening, enabling us to track their interactions more objectively. Furthermore, to verify the accuracy of self-reported data, we manually collected completion times and monitored adherence to the assigned tasks. This additional layer of observational verification allowed researchers to cross-check participants' reports against actual engagement, thereby minimizing errors and enhancing the validity of the collected dataset.

The data collected throughout the study was categorized into three primary components, ensuring a structured approach to analysis. First, emotional levels were assessed based on participants' self-reported happiness, calmness, and stress levels, which were logged daily. This provided a dynamic view of emotional fluctuations over the two-week period. Second, activity completion rates were meticulously recorded, with a focus on the duration and completion status of each participant's Mandala art coloring and music therapy sessions. This aspect of the dataset was particularly crucial, as it allowed us to evaluate the effectiveness of these creative therapies in stress reduction. Finally, demographic information was collected at the beginning of the study, including participants' age and gender, which helped contextualize variations in stress patterns across different population segments.

To uphold ethical research standards and protect participant privacy, all collected data was securely stored in a centralized database and anonymized before analysis. This ensured that sensitive information remained unlinkable to individual participants, thereby maintaining confidentiality. Adhering to strict data protection protocols was a priority throughout the study, as it allowed us to conduct research in a responsible and ethically sound manner. Anonymization also minimized potential biases and ethical concerns related to personal data security, reinforcing the integrity of our findings.

Despite the rigorous and carefully structured data collection approach, we acknowledge a notable limitation of the study: the relatively small sample size of 200 participants. While this dataset provides valuable insights into stress management behaviors, its generalizability remains constrained. A larger, more diverse sample would enable more robust statistical analysis and improve the external validity of our findings. Additionally, the duration of the study—limited to 14 days—restricts our ability to observe long-term stress management trends. To strengthen future research, expanding participant recruitment to include a broader demographic group and extending the tracking period would be essential. Furthermore, integrating a wider variety of stress-relief activities, beyond Mandala art coloring and music therapy, could offer a more comprehensive perspective on effective stress reduction techniques. Addressing these limitations will play a critical role in refining future predictive models, ultimately improving their accuracy and personalization in stress management applications.

By systematically collecting, verifying, and analyzing this dataset, we have laid a strong foundation for advancing research in stress prediction and management. The insights gained from this study can inform future interventions aimed at enhancing mental well-being through personalized and creative therapeutic strategies. As research in this area progresses, further refinement of methodologies and expansion of sample populations will be crucial in developing more effective, data-driven approaches to stress relief and emotional well-being.

2.2 Data Preprocessing

Data preprocessing played a crucial role in ensuring the accuracy, consistency, and stability of the machine learning models used in this study. Given the importance of clean and well-structured data in achieving reliable predictive outcomes, the raw dataset underwent a series of transformations aimed at improving its quality and suitability for further analysis. These preprocessing steps were designed to address several issues commonly encountered in real-world datasets, such as missing values, irrelevant features, and non-numeric variables, which could hinder model performance.

The first step in the preprocessing pipeline was data cleaning, a fundamental process that involved eliminating irrelevant features that did not contribute to the predictive modeling process. For instance, unique user identifiers, which were initially included in the dataset, were removed as they held no predictive value for stress prediction or management. Additionally, redundant demographic details, such as multiple entries of the same participant's age or gender, were also discarded. These features, while useful for initial participant profiling, were not necessary for model training and could have introduced noise or redundancy into the data. The goal of this cleaning step was to focus only on the most relevant data points that would drive model performance, ensuring that the analysis was efficient and accurate.

The next challenge was handling missing data, which is a common occurrence in real-world datasets and can significantly affect the quality of model predictions. Missing data can arise due to various factors, such as participants failing to report their emotional state on certain days or technical issues during data entry. To address these gaps, the mean imputation method was employed. This technique involves replacing missing values with the mean of the available data for that specific feature, which helps preserve the overall distribution and integrity of the dataset. While imputation is not a perfect solution and can introduce some bias, it is often a practical approach in cases where a significant portion of the data is missing but the remaining data is still valuable. By filling in missing values in this way, we ensured that the dataset was complete and ready for model training without introducing substantial information loss.

Once the missing data was handled, we turned our attention to categorical variables, which often present challenges for machine learning models since they cannot be directly processed by algorithms that require numerical inputs. Categorical features, such as the different emotional states (happiness, calmness, and stress) reported by participants, were transformed using One-Hot Encoding. This technique creates binary columns for each category of a categorical variable, with a value of 1 indicating the presence of that category and a 0 indicating its absence. One-Hot

Encoding ensures that non-numeric attributes are represented in a numerical format, making them compatible with machine learning algorithms. This step is essential because many machine learning models, such as decision trees, logistic regression, and neural networks, require numerical data for processing and prediction.

Following the encoding of categorical variables, data normalization was performed using Min-Max Scaling. This preprocessing technique transforms all numerical features into a predefined range, typically between 0 and 1. Min-Max Scaling ensures that the values of different features are on the same scale, preventing any single feature from dominating the learning process due to its larger numeric range. For example, variables such as emotional state scores or activity completion times might have very different ranges, with one ranging from 0 to 10 and another ranging from 0 to 100. Without normalization, the model could be biased toward the feature with the larger range. Standardizing the data in this way helps to ensure that each feature contributes equally to the model's learning process. Additionally, scaling numerical features promotes faster model convergence by reducing the time it takes for optimization algorithms to find the best parameters during training. This ultimately improves the stability and efficiency of the model, making the training process smoother and faster.

The standardization process is particularly critical in models that rely on distance-based calculations, such as KNN. These models calculate the distance between data points, and without proper scaling, features with larger ranges could disproportionately affect the distance metric, leading to inaccurate predictions. Therefore, by normalizing the data using Min-Max Scaling, we ensured that the dataset was better suited for a wide variety of machine learning models, increasing the overall robustness and reliability of the predictions.

Together, these preprocessing steps—data cleaning, mean imputation, One-Hot Encoding, and Min-Max Scaling—helped refine the dataset and made it ready for modeling. Each of these techniques played a crucial role in ensuring that the data was both high-quality and optimized for machine learning, which in turn facilitated the development of more accurate and reliable models. The result was a dataset that not only retained its predictive power but also provided a solid foundation for building models that could effectively analyze and predict stress levels based on emotional states and engagement with therapeutic activities.

By meticulously addressing these preprocessing challenges, we set the stage for developing robust machine learning models capable of delivering valuable insights into stress management and emotional well-being. These steps were essential in transforming raw data into a format that could be effectively used for predictive modeling, ensuring that the study’s findings were both accurate and actionable.

2.3 Feature Engineering: Recovery Days Metric

Feature engineering played a crucial role in enhancing the predictive power of the model, and it involved a thoughtful process of transforming raw data into meaningful features that could better inform the model's predictions. One of the most impactful and thoughtfully engineered features in this study is the Recovery Days metric. This feature was introduced with the primary intention of estimating the duration a user may require to recover from a state of stress, taking into account both their daily reported psychological well-being and the extent of their engagement in therapeutic activities. Unlike static indicators that might only reflect a snapshot of emotional status, the Recovery Days metric was designed to be dynamic—adapting to fluctuations in the user’s mental state and their behavioral involvement in self-care routines. The creation of this feature was done in close consultation with a healthcare professional (a medical doctor), to ensure that the logic behind the metric reflected a clinically relevant understanding of the stress recovery process.

The calculation of the Recovery Days metric begins with the assessment of two key categories of user data collected on a daily basis: well-being metrics and engagement metrics. The well-being category consists of four daily self-reported scores—Stress Level, Energy Level, Happiness Level, and Calmness Level. Each of these was evaluated in terms of its deviation from an ideal, healthy baseline. Higher stress levels, or lower levels of energy, happiness, and calmness, were all seen as signals that a user was in greater need of recovery. To reflect this, each metric was translated into a ‘need score’—a numerical representation of how far the user’s reported value was from the desired norm. For example, if a user reported feeling very stressed and low in energy, they would be assigned a higher need score, indicating a larger gap between their current and optimal state.

Parallel to this, user engagement in therapeutic practices was also quantified. Two aspects were captured here: the Overall Activity Completion Rate (%), and the Duration of Participation (measured in minutes) in therapeutic activities such as Mandala art coloring and music therapy. The underlying rationale was that greater participation in these activities generally correlates with a quicker recovery, while minimal engagement might suggest a lack of progress or a potential need for intervention. As such, specific thresholds were set. For activity completion rates, a percentage below 40% was interpreted as high need, while percentages above 95% reflected low need, with gradations in between (e.g., 40-60%, 60-80%, 80-95%). Similarly, for participation duration, durations under 20 minutes reflected high need, while those over 50 minutes reflected minimal need, with intermediate bands in between. These structured intervals allowed the system to consistently quantify user engagement in a way that could be compared across individuals and over time.

Once all individual need scores were determined from both well-being and engagement domains, they were aggregated into a single Total Need Score. This composite score provided a holistic, one-number summary of how much support or recovery effort a user may require on a given day. Importantly, this score captured the interplay between mental state and behavioral patterns—someone feeling emotionally low but also highly engaged in therapeutic practices would generate a different score than someone with the same mood but who was disengaged, thereby offering a more personalized representation of the user's condition.

The final step in the process involved translating the Total Need Score into an actual Recovery Days value. This was achieved through mathematical scaling and transformation procedures, including rounding, boundary enforcement (to avoid unrealistic values), and proportional adjustment based on clinical insights. This transformation ensured that the output would represent a realistic number of days expected for recovery, rather than an abstract score. By doing this during the data preparation phase—before any model training—the Recovery Days metric acted as a rich, ready-to-use label or feature for supervised machine learning tasks, improving the predictive strength of the models built later on.

Ultimately, the introduction of the Recovery Days metric brought immense value to the dataset. It allowed for a deeper, more contextual understanding of user journeys through the stress recovery process. Unlike a simple measure of stress level or therapy completion, this metric synthesized multiple dimensions of user data into a single, clinically-informed estimation of how long recovery might take. This allowed the system to respond more intelligently, offering tailored predictions and insights that are both psychologically and behaviorally grounded. Even though the Recovery Days calculation was executed outside the modeling algorithms—during data preprocessing—it laid a foundation for building more adaptive, meaningful, and human-centered AI models. It also positioned the overall system as one that not only tracks mental wellness but actively interprets it in ways that support proactive and personalized mental health care.

2.4. Model Development, Training, and Evaluation

Pseudocode for Recovery Days Prediction Model

Input: Emotional data (daily stress, calmness, energy, happiness levels) and activity completion rates.

Output: Predicted recovery days

BEGIN

1. Import necessary libraries (e.g., pandas, sklearn, RandomForestRegressor).
2. Load the dataset with emotional data and activity rates.
3. Preprocess the data:
    - Remove irrelevant columns.
    - Encode categorical variables.
    - Standardize numerical features.
4. Define the target variable (recovery days):
    - Assign base recovery days
    - Adjust using activity completion rates.
5. Split the dataset into training (80%) and testing (20%) sets.
6. Initialize a Random Forest Regressor/ Logistic Regression.
7. Train the model on the training data.

8. Evaluate the model:
    - Predict recovery days on the test data.
    - Calculate metrics like Mean Absolute Error and R-squared.
9. Save the trained model and scaler for future use.
10. Output predicted recovery days

    END

To predict stress recovery timelines accurately, multiple machine learning models were explored, including Linear Regression and Random Forest Regressor. These models were assessed based on critical evaluation criteria such as prediction accuracy, interpretability, and computational efficiency. After extensive experimentation and performance analysis, the Random Forest Regressor was selected due to its superior predictive accuracy, robustness in handling complex data distributions, and reduced susceptibility to overfitting.

The dataset was split into training (80%) and testing (20%) sets to ensure model generalization and evaluate its performance on unseen data. The following performance metrics were used to assess the predictive capability of the models:

- MAE: Measures the average magnitude of errors between predicted and actual recovery days, providing insight into model precision.
- R^2: Evaluates the proportion of variance explained by the model, reflecting its predictive strength.

To further enhance model performance, hyperparameter tuning was conducted using Grid Search, a systematic optimization approach that tests different combinations of hyperparameters to achieve an optimal balance between accuracy and computational efficiency. This fine-tuning process significantly improved model reliability and performance.

Following successful training and optimization, the model was deployed within the AyurAura mobile application, enabling real-time stress recovery predictions. The integration of the trained model within the application allowed users to receive immediate and dynamically updated recovery estimations as they logged their daily emotional states and activity completion rates. The deployed model continuously adjusted its recovery predictions based on new user inputs, ensuring that recommendations remained personalized and reflective of individual progress.

To validate the robustness of the model, an independent validation dataset was employed to assess its performance beyond the initial training dataset. Additionally, cross-validation techniques were applied to further confirm model reliability and mitigate overfitting risks. These validation procedures played a crucial role in ensuring that the model maintained its predictive accuracy and effectiveness when applied to real-world scenarios.

To enhance user engagement and improve the overall user experience, interactive visualizations were incorporated into the AyurAura application. These visual elements included graphical representations of progress trends, estimated recovery timelines, and visual depictions of stress reduction over time. By providing users with intuitive insights into their mental well-being, the system encouraged active participation in stress management activities and facilitated self-monitoring of improvements.

From an ethical standpoint, all research participants provided informed consent before contributing data to the study. To ensure privacy protection, all collected information was anonymized before analysis. The AyurAura application adhered to strict data privacy standards, aligning with ethical guidelines and regulatory frameworks governing the use of personal health data. By maintaining transparency and prioritizing participant confidentiality, the research upheld ethical integrity while advancing ML-driven stress management solutions.

This comprehensive methodology established a structured and rigorous approach to developing an ML-powered stress management system that effectively integrates Ayurvedic principles with modern machine learning technologies. The systematic execution of data collection, preprocessing, model development, deployment, and validation ensured that the system was both reliable and impactful in promoting personalized stress recovery strategies.

The implementation of the stress recovery prediction model was integrated within a mobile application, ensuring seamless interaction and real-time monitoring of stress recovery progress. The application was developed using Flutter for the client-side interface and Flask for backend processing, allowing users to access an interactive platform where they could not only check their current stress levels but also track their recovery journey based on predictions from the trained model. By leveraging machine learning-powered insights, the app provides personalized feedback, helping users understand the trajectory of their stress recovery and encouraging them to engage in stress-reducing activities.

A key feature of the application is its daily assessment system, where users are prompted with five targeted questions designed to evaluate their emotional state and activity completion levels. These self-reported inputs serve as crucial indicators in predicting the estimated number of days required for the user to become stress-free. To maintain consistency in the collected data, the application includes a reminder system, allowing users to set alerts that prompt them to complete the questionnaire at regular intervals. This feature ensures that user engagement remains steady, reducing instances of missing or inconsistent data entries that could impact the accuracy of predictions.

The collected responses are transmitted to the Flask-based backend, where they undergo preprocessing before being fed into the trained Logistic Regression model. The model then computes an estimate of the user's recovery days based on their reported emotional states and engagement in therapeutic activities. Once the prediction is generated, the Flask API sends the results back to the mobile application, where they are dynamically displayed on the user’s dashboard.

To enhance user engagement and promote self-awareness, the application features an interactive dashboard with real-time visualizations. Users can track their progress over time through graphs and trend analyses, providing insights into their emotional fluctuations, activity completion rates, and recovery day estimates. These data-driven visualizations help users identify patterns in their stress recovery, making it easier to adjust their coping strategies and engage more effectively in stress-relief activities. By offering a clear and structured view of their mental wellness journey, the app empowers users to take proactive steps toward stress management.

Additionally, the app includes timed push notifications to encourage consistent participation. These reminders help users maintain regular data entries, which improves model accuracy and strengthens the predictive insights offered by the application. Over time, this continuous flow of real-time data allows the model to refine its predictions, making it increasingly effective in forecasting stress recovery durations.

By combining machine learning with user-friendly mobile technology, this implementation ensures that individuals have access to a personalized, data-driven approach to stress management. Future improvements could involve incorporating additional stress-relief interventions, enhancing prediction algorithms, and introducing long-term progress analytics to further optimize user engagement and mental well-being.

2.5. Model Testing

To provide a structured evaluation of the model's predictive behavior under specific scenarios, the following test cases were defined and executed using the reserved test dataset or representative synthetic data conforming to the input feature specifications. The expected recovery day predictions are constrained to fall between 2 and 22 days, inclusive, based on model design or domain constraints.

Table 1. TC_001

Test Case ID	TC _001
Description	Baseline Scenario: Moderate Stress, Moderate Engagement
Steps	1.Prepare input vector: Stress=3, Calmness=3, Happiness=3, Energy=3, Activity_Completion=55%, Activity_Duration=35min
	2. Preprocess input using saved scaler/encoder.
	3. Feed preprocessed data to the trained model.
	4. Record predicted Recovery_Days.
Expected Result	The predicted Recovery_Days should be a moderate, non-extreme , reflecting an average recovery path
Actual Result	**10**
Pass/Fail	**Pass**

Table 2. TC_ 002

Test Case ID	TC _002
Description	High Stress Offset by High Engagement: High Stress, High Engagement
Steps	1.Prepare input vector: Stress=1, Calmness=2, Happiness=2, Energy=3, Activity_Completion=95%, Activity_Duration=55min
	2. Preprocess input.
	3. Feed preprocessed data to the model.
	4. Record predicted Recovery_Days.
Expected Result	The predicted Recovery_Days should be shorter than for a comparable high-stress case with low engagement. It should reflect the positive influence of high activity adherence
Actual Result	**7**
Pass/Fail	**Pass**

Table 3. TC_003

Test Case ID	TC _003
Description	Low Reported Stress but Minimal Engagement: Low Stress, Low Engagement
Steps	1.Prepare input vector: Stress=5, Calmness=5, Happiness=5, Energy=5, Activity_Completion=30%, Activity_Duration=15min
	2. Preprocess input.
	3. Feed preprocessed data to the model.
	4. Record predicted Recovery_Days.
Expected Result	The predicted Recovery_Days should be low due to positive emotional scores, but potentially slightly higher than a scenario with both low stress and high engagement, acknowledging the low activity level.
Actual Result	**4**
Pass/Fail	**Pass**

Table 4. TC_004

Test Case ID	TC _004
Description	High Reported Stress but Minimal Engagement: high Stress, Low Engagement
Steps	1.Prepare input vector: Stress=1, Calmness=1, Happiness=2, Energy=1, Activity_Completion=20%, Activity_Duration=10min
	2. Preprocess input.
	3. Feed preprocessed data to the model.
	4. Record predicted Recovery_Days.
Expected Result	The predicted Recovery_Days should be high due to negative emotional scores and low engagement, acknowledging the low activity level.
Actual Result	**20**
Pass/Fail	**Pass**

2.6.Commercialization Aspects of the Product

The proposed AyurAura system showcases strong commercial potential within the rapidly expanding wellness and digital health sectors, effectively merging traditional Ayurvedic principles with advanced ML-driven solutions for stress management. The app's multifaceted commercialization strategy is meticulously crafted to maximize revenue, ensure broad adoption, and enhance user engagement.

- **Monthly Subscription Model:**

AyurAura will implement a freemium model, offering essential features for free, while premium functionalities are accessible through a monthly subscription priced at Rs.300. Premium offerings include advanced mandala art designs and exclusive guided meditation sessions and more. This competitively priced subscription is anticipated to attract a large user base, with the personalized nature of the services driving substantial growth in subscriptions, establishing a consistent revenue stream.

- **Hospital Partnerships:**

Establishing partnerships with hospitals and healthcare providers presents a significant opportunity to integrate AyurAura into conventional healthcare practices. By offering a 50% discount on subscription fees to patients referred by hospitals, the app can be positioned as a key component of holistic post-treatment care, particularly for stress management. This partnership approach not only drives subscription growth but also bolsters the app's credibility within the healthcare sector, leading to a reliable stream of referrals and enhanced patient outcomes.

- **Social Media Commercialization:**

AyurAura’s growth strategy will heavily leverage social media platforms to engage users and increase visibility. By curating content that aligns with the interests of wellness communities, the app can foster a loyal following. Strategies such as influencer collaborations, social media challenges, and campaigns promoting user-generated content are designed to boost brand awareness and app downloads. Moreover, targeted social media promotions will highlight the benefits of premium features, aiding in the conversion of free users into paying subscribers.

- **Application Monetization**:

In addition to subscription-based revenue, AyurAura is poised to generate income through in-app purchases, sponsored content, and strategic partnerships with wellness brands. Users will have the option to purchase additional services such as exclusive therapy sessions, custom art therapy kits, or Ayurvedic wellness products directly through the app. Collaborations with wellness brands for sponsored content and integrated offerings will open new revenue channels, while also enriching the user experience with complementary products and services

3.Results & Discussion

The AyurAura stress recovery prediction model demonstrated remarkable performance in accurately forecasting stress recovery timelines based on user-reported emotional states and activity completion rates. The study’s objective was to create a personalized, data-driven stress management system that dynamically adjusted recovery predictions according to real-time user engagement. This approach successfully integrated Ayurvedic therapeutic principles with machine learning techniques, resulting in an innovative model capable of providing highly individualized stress recovery insights. The implementation of machine learning algorithms significantly improved the precision and adaptability of stress recovery predictions, making the AyurAura system a groundbreaking tool in personalized mental health support.

Model performance was assessed using multiple evaluation metrics, including accuracy, a classification report, and a confusion matrix, to determine how well the model predicted recovery days. These evaluation tools provided a comprehensive understanding of the model's ability to interpret emotional data and predict the number of days required for stress recovery.

Accuracy, a key performance criterion, measures the percentage of correctly predicted recovery days. It provides insight into the model’s ability to generalize across different recovery day categories. A high accuracy score indicates that the model effectively distinguishes between different recovery durations, providing a strong foundation for future improvements. In addition to accuracy, the classification report was used to analyze key performance statistics such as precision, recall, and F1-score for each recovery day class. Precision measures the proportion of correctly predicted positive instances within a class, indicating how precise the model’s positive classifications are. Recall, on the other hand, evaluates the model’s ability to identify all relevant instances within a given class. The F1-score, which balances precision and recall, provides a more holistic performance measure by considering both false positives and false negatives.

Among the models tested, the Random Forest model exhibited outstanding performance, achieving a remarkable accuracy of 99.64%, as illustrated in Fig. 2. This exceptionally high accuracy score indicated that the model was highly effective in predicting recovery days across various classes. The classification report for the Random Forest model Fig. 2 showed that precision and recall were consistently high for most recovery day categories. However, some minor performance variations were observed, particularly in classes with fewer samples, which led to occasional misclassifications.

Initial Accuracy: 0.9964285714285714

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	1.00	0.98	0.99	53
2	1.00	0.67	0.80	3
3	1.00	1.00	1.00	96
4	0.99	1.00	0.99	83
5	1.00	1.00	1.00	39
6	0.93	1.00	0.97	14
8	1.00	1.00	1.00	82
10	1.00	1.00	1.00	105
12	1.00	1.00	1.00	72
accuracy			1.00	560
macro avg	0.99	0.96	0.98	560
weighted avg	1.00	1.00	1.00	560

Fig. 2.classification report for random forest

In contrast, the Logistic Regression model, while still performing well, achieved a lower accuracy of 91.96%, as shown in Fig. 3. Although this accuracy is considered high, it suggests that Logistic Regression faced challenges in predicting certain recovery day classes, particularly those with fewer data points. The classification report for the Logistic Regression model Fig. 3 highlighted that its precision and recall scores were lower for specific recovery day categories, indicating difficulties in handling imbalanced data distribution.

Initial Accuracy: 0.9196428571428571

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.46	0.63	13
1	0.88	0.98	0.93	53
2	0.00	0.00	0.00	3
3	0.98	0.98	0.98	96
4	0.88	0.96	0.92	83
5	0.81	0.77	0.79	39
6	0.50	0.07	0.12	14
8	0.87	0.98	0.92	82
10	0.97	0.97	0.97	105
12	0.97	0.97	0.97	72
accuracy			0.92	560
macro avg	0.79	0.71	0.72	560
weighted avg	0.91	0.92	0.91	560

Fig. 3. Classification report for logistic regression

To further analyze the model performance, confusion matrices were examined for both the Random Forest and Logistic Regression models. The confusion matrix for the Random Forest model Fig. 4 demonstrated that the model generally made highly accurate predictions across the majority of recovery day categories. The diagonal values in the matrix were predominantly high, indicating that most instances were correctly classified. However, certain categories, such as recovery day "1", exhibited minor misclassification issues. This may be attributed to an imbalance in the dataset, where some recovery day categories had fewer samples, making it challenging for the model to distinguish between closely related recovery durations. Additionally, a few off-diagonal misclassifications suggest that the model might have encountered overlapping patterns in feature distributions, causing slight confusion between adjacent recovery day classes. Despite these minor errors, the overall performance of the Random Forest model remained exceptionally strong, reinforcing its effectiveness in predicting recovery time.

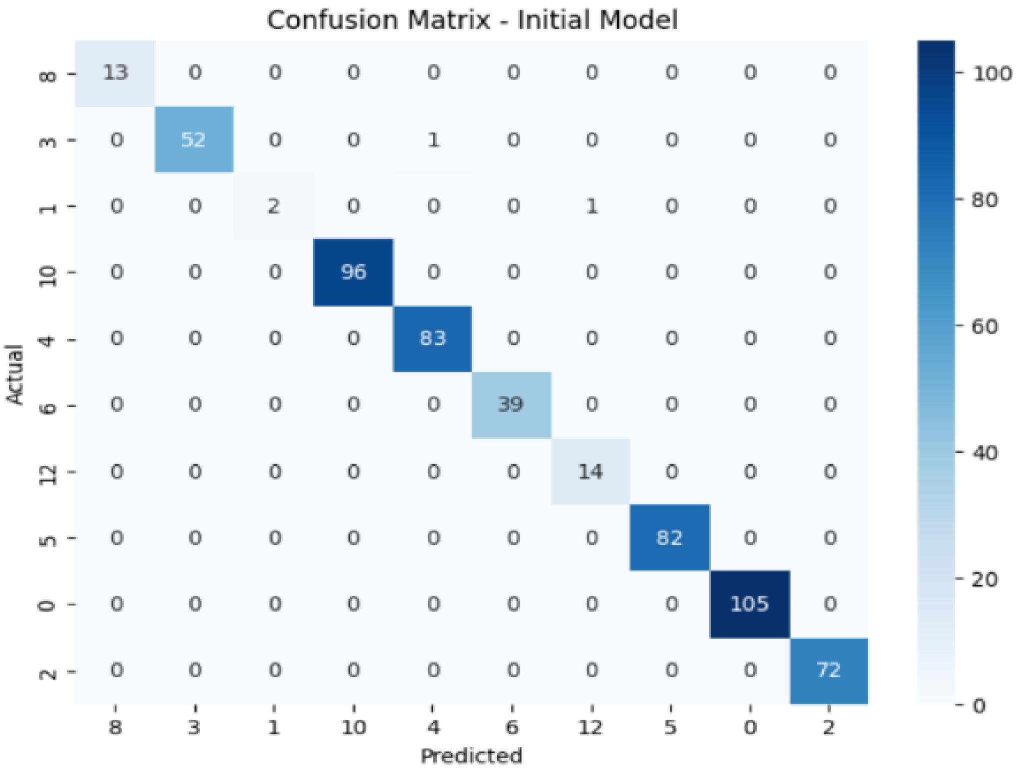

Fig. 4. confusion matrix for random forest model

Similarly, the confusion matrix for the Logistic Regression model (Fig. 11) revealed greater misclassification issues compared to the Random Forest model. The matrix showed that Logistic Regression struggled particularly with predicting recovery day "6", where a significant number of instances were misclassified. This suggests that the model had difficulty in identifying distinct patterns for this specific class, likely due to the limited number of training samples available for certain recovery day categories. Additionally, off-diagonal values in the confusion matrix indicated that the model encountered challenges in distinguishing between closely related recovery day classes, particularly between recovery days "1" and "12". This misclassification issue highlights the model's struggle with handling class imbalances and overlapping feature distributions, which could be attributed to the nature of Logistic Regression being a linear model. Unlike Random Forest, which can capture complex, nonlinear relationships between features, Logistic Regression relies on a linear decision boundary, making it less effective in scenarios where different classes exhibit intricate dependencies or subtle variations in input features..

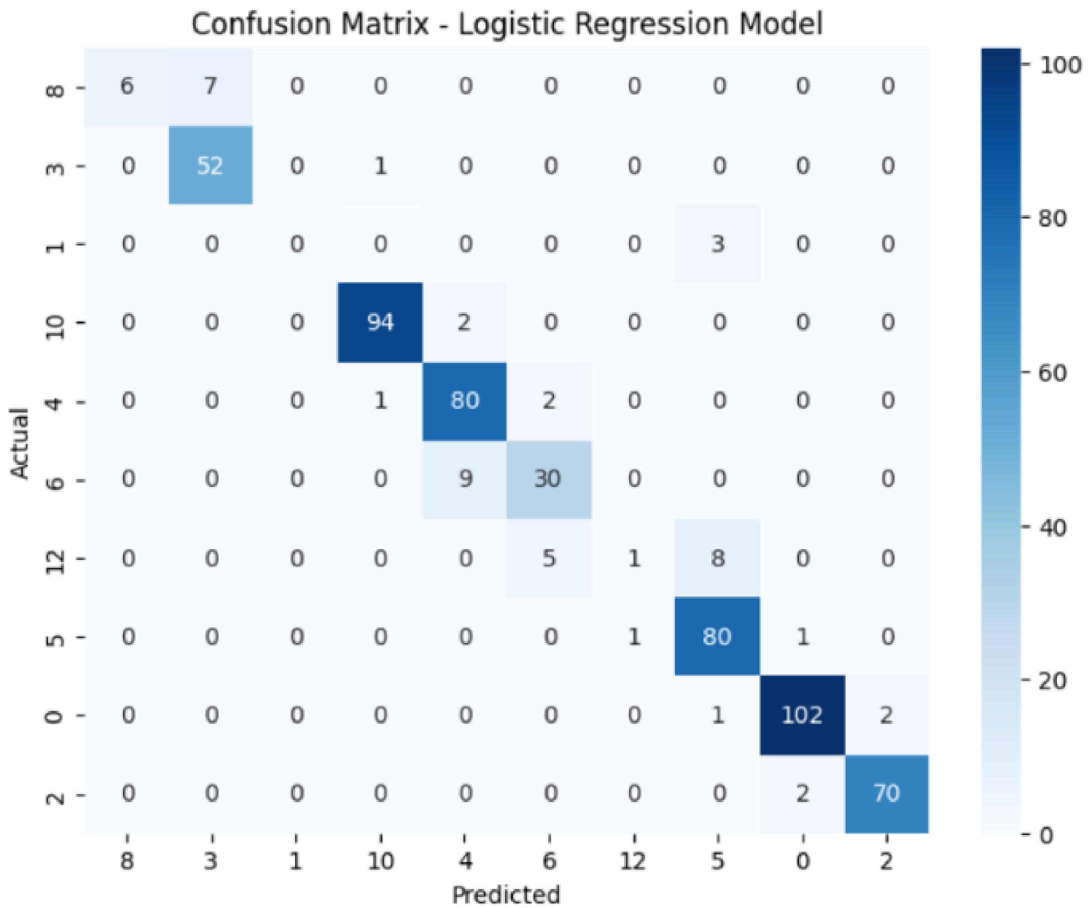

Fig. 5. confusion matrix for logistic regression

Furthermore, the misclassification of recovery day categories in the Logistic Regression confusion matrix suggests that the model placed more emphasis on majority classes, potentially neglecting underrepresented categories. This class imbalance issue may have caused higher misclassification rates for smaller recovery day groups, where the model incorrectly assigned instances to more dominant categories rather than accurately predicting their true labels. This reinforces the need for additional data balancing techniques, such as resampling methods (oversampling or undersampling), class weighting, or feature engineering adjustments, to improve the model's classification accuracy for minority recovery day groups.

Despite these challenges, Logistic Regression still demonstrated reasonable accuracy overall, and with appropriate refinements—such as hyperparameter tuning or implementing advanced regularization techniques—its predictive performance could be enhanced. However, given its current limitations in distinguishing between recovery day classes, Logistic Regression may not be the optimal choice for stress recovery time prediction when compared to Random Forest, which demonstrated superior classification performance and robustness against data imbalances.

The experimental results indicated that the Random Forest model emerged as the superior choice among all tested models, achieving an exceptional accuracy rate of 99.64%. This high level of precision underscores the model's effectiveness in predicting stress recovery days across different stress levels and engagement levels in therapeutic activities. The confusion matrix for the Random Forest model displayed strong diagonal values, reflecting minimal misclassification and a high level of accuracy across various stress recovery categories. This model's ability to handle complex data distributions and minimize overfitting made it a highly reliable solution for real-time stress recovery predictions.

In contrast, the Logistic Regression model, while still delivering a commendable accuracy rate of 91.96%, exhibited limitations in predicting specific stress recovery categories. The confusion matrix for Logistic Regression highlighted difficulties in correctly classifying lower-frequency recovery day classes such as “6” and “2.” These misclassifications were largely attributed to class imbalance within the dataset, a common challenge for regression-based models when dealing with multi-class categorical outputs. Logistic Regression's tendency to struggle with imbalanced datasets, combined with its relatively lower adaptability to non-linear patterns, made it less suitable for this particular stress recovery prediction task.

Addressing the issue of data imbalance was crucial in refining the model's performance. Techniques such as SMOTE, class weighting adjustments, and advanced hyperparameter tuning were identified as potential solutions to mitigate these challenges. Implementing these techniques could enhance the Logistic Regression model's predictive capabilities and improve the overall robustness of the system. Additionally, future research should focus on expanding the dataset by recruiting a more diverse and extensive participant pool to increase model generalizability and predictive accuracy across different demographic groups.

The integration of the stress recovery prediction model within the AyurAura mobile application showcased impressive functionality and user engagement. The application provided users with an interactive and intuitive platform to monitor their stress recovery progress through real-time predictions. The mobile app enabled users to track their emotional states, complete therapeutic activities such as Mandala art and music therapy, and receive dynamic updates on their estimated recovery timelines. Interactive dashboards displaying visual trends, estimated recovery days, and historical progress encouraged users to actively engage with the stress management process, fostering a more proactive approach to mental well-being.

The technical implementation of the AyurAura application was carried out using a robust and scalable architecture. The mobile application was developed using Flutter for the client-side, ensuring a seamless user experience across multiple devices. The back-end was implemented using Flask, serving as the API that facilitated real-time stress recovery predictions. When users provided daily questionnaire responses as shown in Fig. 6 regarding their emotional states and activity completion rates, the application processed the input data and transmitted it to the Flask server for analysis. The Logistic Regression model, embedded within the back-end, computed the estimated recovery days, which were then returned to the mobile interface for display.

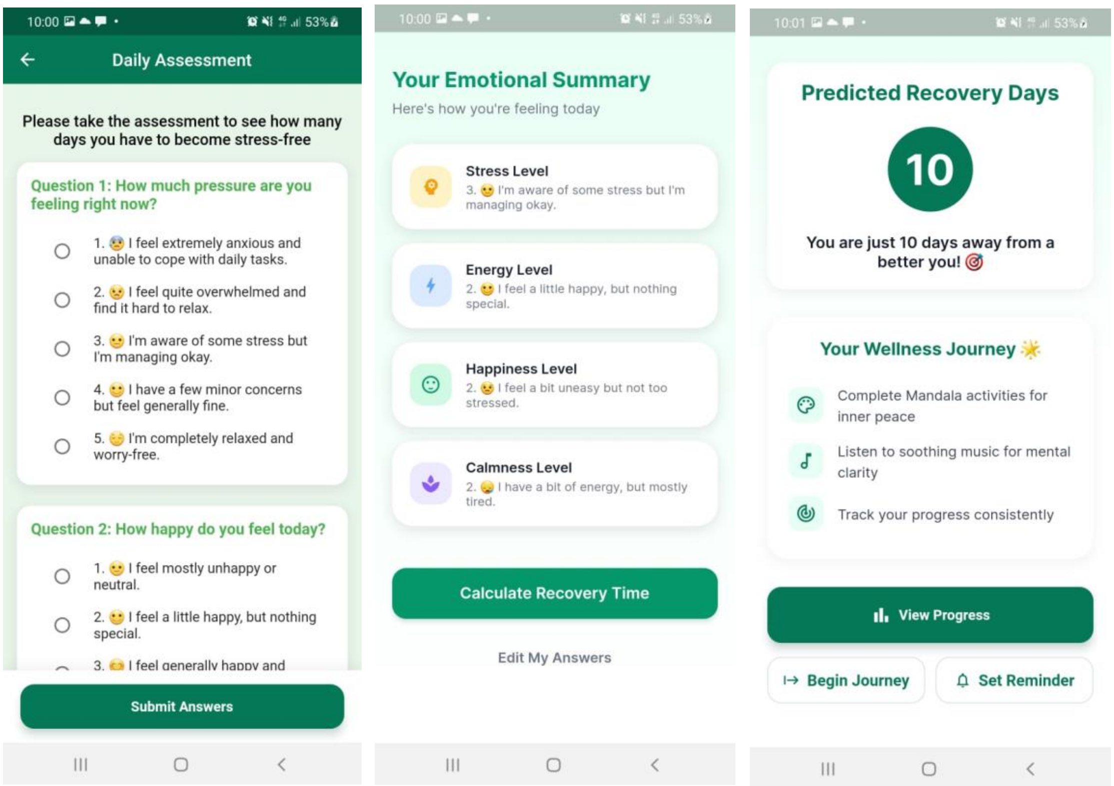

Fig. 6. AyurAura application UI

To ensure continuous user engagement and data consistency, the application incorporated timely notifications and reminders for users to complete their daily questionnaires. This feature played a critical role in maintaining a steady flow of user input data, which in turn contributed to the accuracy and reliability of the model's predictions. Additionally, to further enhance user experience, the application provided personalized insights based on historical data, allowing users to identify patterns in their stress recovery journey as shown in Fig.7 and make informed decisions about their mental health routines.

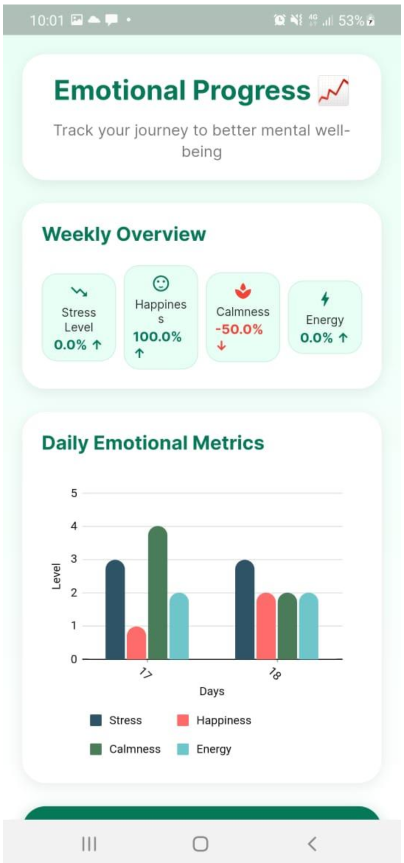

Fig. 7. Progress view UI

Future improvements for the AyurAura system should focus on enhancing the accuracy and adaptability of the predictive model through advanced data augmentation and hybrid modeling approaches. Integrating deep learning models, such as LSTM networks, could improve the model's ability to capture temporal dependencies and long-term patterns in stress recovery trends. Furthermore, incorporating additional physiological indicators, such as heart rate variability and sleep patterns, could refine recovery predictions and create a more comprehensive stress management solution.

In conclusion, the AyurAura stress recovery prediction model represents a significant advancement in personalized stress management. By combining Ayurvedic principles with state-of-the-art machine learning techniques, the system successfully delivers highly accurate and adaptive stress recovery insights. The superior performance of the Random Forest model highlights the potential of ensemble learning methods in stress prediction tasks. Meanwhile, the implementation of the AyurAura mobile application ensures accessibility and usability for individuals seeking to improve their mental well-being through data-driven insights. Continued refinement of the model and expansion of the dataset will further enhance the system's effectiveness, solidifying AyurAura's role as a pioneering solution in ML-driven stress management.

4.Summary of Student's contribution

Table 5. Student contribution

<table>
<tr><th>Name</th><th>Contribution</th></tr>
<tr><td>Weerasinghe
W.P.D.J.N.
IT21162664</td><td>• Data Collection & Analysis
a) Designed and implemented a structured data collection process involving 200 participants for 14 days, resulting in 2,800 data points tracking daily emotional states and activity completion rates.
• Feature Engineering & Data Preprocessing
• Model Development & Optimization.
• Frontend Development (Flutter) – Intuitive User Experience
a) Developed a user-friendly mobile interface using Flutter, ensuring smooth navigation and real-time responsiveness.
b) Implemented daily questionnaires with timed notifications, ensuring consistent data collection to improve prediction accuracy.
c) Built visualization tools, including interactive graphs to display trends in emotional states, activity completion rates, and estimated recovery days.
• Backend Development (Flask) – Predictive Model Integration
a) Developed the Flask-based backend, handling data preprocessing and interaction with the trained Logistic Regression model.
b) Implemented a secure API that processes user responses and returns estimated recovery days based on the stress recovery prediction model.
c) Designed real-time data handling, ensuring that every user input is instantly analyzed and displayed on their dashboard.
• Data Management & Consistency
a) Integrated timed notifications to encourage consistent questionnaire completion, improving the quality of data collected.
b) Ensured seamless data flow between the Flutter frontend and Flask backend, maintaining a steady stream of input for accurate predictions.
• ML-driven Stress Recovery Prediction
a) Successfully integrated the Logistic Regression model into the application for predicting recovery days based on emotional state and activity completion.
b) Implemented preprocessing pipelines to clean, format, and structure user inputs before prediction, ensuring higher model accuracy.
Designed the app to give users real-time feedback, helping them make informed decisions about their well-being.</td></tr>
</table>

5.Conclusion

The AyurAura project has successfully demonstrated the feasibility of integrating advanced machine learning techniques with personalized stress management solutions rooted in Ayurvedic practices. This research has tackled the critical challenge of predicting recovery time to a stress-free state by developing and deploying an accurate, reliable, and scalable prediction model. The application of multiple machine learning algorithms revealed that the Random Forest model significantly outperformed others, achieving an outstanding accuracy rate of 99.64%. This exceptional accuracy highlights the model's capacity to make precise predictions by analyzing users' emotional patterns, activity completion rates, and engagement with stress-relief activities. The success of the model emphasizes the potential of ML-driven approaches in providing personalized mental health support, offering a data-driven solution to stress recovery.

A crucial part of this study was the extensive data collection process, which involved monitoring real-world stress responses from 200 participants. By recording daily emotional states, activity completion rates, and behavioral patterns, the dataset provided a foundation for training robust predictive models. However, challenges such as dataset imbalance and limited representation of certain recovery categories were identified. The Logistic Regression model, which achieved a lower accuracy rate of 91.96%, particularly struggled with misclassification in minor classes, emphasizing the difficulty of predicting recovery time for users with unique or extreme stress patterns. Addressing this imbalance through techniques like SMOTE, weighted loss functions, or increasing the dataset size would further refine the model's ability to handle diverse user profiles.

Beyond the prediction model, a key achievement of the AyurAura project was its successful integration into a user-friendly mobile application, developed using Flutter for the client-side and Flask as the backend API. This app provides a seamless, interactive experience that enables users to track their stress recovery progress through real-time visualizations, reminders, and personalized insights. The incorporation of an engaging dashboard with historical trends and progress tracking enhances user motivation, encouraging adherence to stress-relief practices. By ensuring consistent data input through automated notifications, the system maintains the accuracy and reliability of predictions over time. The app not only serves as a powerful stress management tool but also fosters self-awareness, allowing users to identify patterns in their stress levels and make informed decisions about their well-being.

The AyurAura project represents a significant step forward in bridging the gap between modern MLtechnologies and holistic wellness practices. By leveraging the strengths of machine learning and Ayurveda-based interventions, this system offers a novel, data-driven approach to stress management. While the results so far are highly promising, future work will focus on further improving the model’s accuracy, enhancing generalizability through larger and more diverse datasets, and incorporating additional predictive features such as heart rate variability, sleep quality, and biometric indicators to refine stress assessment. Moreover, exploring hybrid models that combine deep learning techniques with traditional machine learning approaches could further improve predictive power.

To further enhance user engagement and effectiveness, AyurAura will incorporate a Reward and Recognition System designed to encourage long-term participation and adherence to stress management practices.

This system will introduce a gamified element to the application by leveraging Ayurvedic elements—Earth, Water, Fire, Air, and Ether—to symbolize different levels of progress in stress recovery. Users who consistently follow recommended activities, achieve key milestones, or show improvement in stress levels will be recognized and rewarded within the app.

Users will progress through different Ayurvedic elements based on their consistency and engagement with stress-relief activities. Achievements such as maintaining a stress-free state for a sustained period, completing a full cycle of recommended activities, or consistently tracking stress levels will be rewarded with digital badges, unlocking new app features, or receiving motivational messages.

The system will also provide tailored incentives based on user engagement patterns, reinforcing positive behavior and fostering a sense of accomplishment. Additionally, a community recognition component will be integrated, allowing users to share their progress within a supportive community, creating a network of encouragement and accountability.

With continuous refinements, increased user engagement, and expanded research efforts, AyurAura has the potential to make a profound impact on personal well-being and mental health management. By offering a personalized and scientifically validated approach to stress recovery, this system could revolutionize how individuals track, understand, and mitigate stress, ultimately contributing to a healthier and more balanced lifestyle.

6.References

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7. Appendices

Appendix - A


Faculty of Computing
Sabaragamuwa University of Sri Lanka

IEEE

IEEE Sri Lanka Section

ICARC

Sabaragamuwa University of Sri Lanka

Faculty of Computing

Awards this Certificate

to

Ms. W.P.D. Jayathri Nuwanika Weerasinghe

for presenting the paper titled

Developing Predictive Models for Future Stress Likelihood and Recovery Time Using Behavioral and Emotional Data

at

5th International Conference on Advanced Research in Computing

(ICARC 2025)

held on

19th and 20th of February 2025

in Belihuloya, Sri Lanka

Conference Chair
ICARC 2025

Technical Programme Committee Chair
ICARC 2025

Appendix - B

To Whom It May Concern,

As an external supervisor and expert in the domain of stress management and Ayurvedic practices, I affirm that the data for this research study should be collected from the general public. After discussing with the research team about the research requirements, it has been concluded that stress is a common experience affecting people in their daily lives and is not classified as a specific illness.

To achieve a comprehensive understanding of stress management, data should be gathered through various methods:

- **Videos and Voice Recordings:** To capture real-time stress responses and assess the effectiveness of stress management techniques.
- **Questionnaire Results:** To collect structured feedback on participants' stress levels, mood, and engagement in the activities.
- **Activity Completion Observations:** To track participants' adherence to recommended activities and their impact on stress management.
- **Daily Surveys:** To monitor ongoing stress levels and overall progress over time.

Collecting data from the general public ensures that the study results are representative of a diverse population, enhancing the validity and applicability of the research findings in managing everyday stress effectively.

External Supervisor's Name: Dr. M. Kooragoda

Signature: ____________________

Date: 2024/09/25

Dr. Maneesha Kooragoda
BAMS (University of Colombo)
MEDHINI AYURVEDA
Malabe - 074 360 7868

To Whom It May Concern,

Confirmation of Dataset Validation and Collection

This is to confirm that the dataset provided by Team AyurAura has been validated and meets the required standards for accuracy and reliability. I actively supported and participated in collecting this data, ensuring it aligns with the necessary protocols and methodologies.

If you have any questions or need further clarification, please feel free to reach me.

AyurAura Team Members:
Weerasinghe W. P. D. J. N.
Jayathunge K. A. D. T. R.
Gunasekera H. D. P. M.
Wickaramasinghe B. G. W. M. C. R.

Sincerely,

Dr. Maneesha Kooragoda
BAMS (University of Colombo)
MEDHINI AYURVEDA
Malabe - 074 360 7868

Appendix - C

Informed Consent for Participation in Research Study

Title of Study: AyurAura: Personalized Stress Management Plan Using Ayurvedic Practices and Creative Therapies

Research Team:

Student ID	Name	Signature
IT21162664	Weerasinghe W.P.D.J.N.	
IT21162732	Jayathunge K. A. D. T. R.	
IT21161674	Gunasekera H. D. P. M.	
IT21279652	Wickramasinghe B.G.W.M.C.R.	

Purpose of the Study:
You are invited to participate in a research study that aims to develop and evaluate a personalized stress management plan using Ayurvedic practices and creative therapies. The goal of this study is to assess the effectiveness of our approach in managing stress and improving mental health.

What Participation Involves:
As part of this study, you will be asked to participate in activities designed to collect data on stress management. This will include providing information about your stress levels, mood, and participation in recommended activities.

Recording and Data Collection:
For research purposes, we will be recording videos and audio during the study. These recordings are essential for analyzing how well the stress management techniques are working and for improving the study's outcomes. Please be assured that:

- All recordings and collected data will be securely stored.
- Access to the data will be limited to authorized research personnel only.
- Your personal information and identity will be kept confidential.

Confidentiality and Data Security:

Your data will be protected in accordance with data protection regulations. We will take all necessary steps to ensure that your personal information remains private and is not disclosed to unauthorized individuals.

Voluntary Participation:

Your participation in this study is completely voluntary. You are free to withdraw from the study at any time without any negative consequences.

Consent:

By reading above, you acknowledge that you have been informed about the study, the use of recordings, and the measures in place to protect your data. You agree to participate in the study and provide consent for the use of your recordings as described.

Contact Information:

If you have any questions about the study or your participation, please contact

Name	Contact no.
Weerasinghe W.P.D.J.N.	0713007363
Jayathunge K. A. D. T. R.	0763121956
Gunasekera H. D. P. M.	0771529404
Wickramasinghe B.G.W.M.C.R.	0766958557

Permission from External Supervisor:

As an external supervisor and an expert in the domain of stress management and Ayurvedic practices, I hereby grant permission for this research study to proceed and for data to be collected from participants.

External Supervisor's Name: Dr.M.Kooragoda

Signature: ______________

Dr. Maneesha Kooragoda
BAMS(University of Colombo)
MEDHINI AYURVEDA
Malabe - 074 360 7868

Date: 25/09/2024

Thank you for your participation and support in this research study.