Predicting Future Stress Likelihood and a Motivational Chatbot.

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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 AI-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 AI and 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 AI-driven recommendations. AyurAura's AI models analyze user data from questionnaires, eye-blinking rates, music therapy engagement, and daily emotional tracking to refine stress predictions and anticipate future stress likelihood based on behavioral patterns. A user-friendly interface enables seamless data reporting and visualization.

By combining holistic healing with AI-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
KNN	K-Nearest Neighbors
API	Application Programming Interface
UI	User Interface
RHR	Resting Heart Rate
TST	Total Sleep Time
IEEE	Institute of Electrical and Electronics Engineers

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1.Introduction

1.1.Background

Stress is a natural and fundamental response to perceived challenges or demands, playing a vital role in human survival. When faced with a threat, the body initiates a complex cascade of physiological and psychological reactions designed to prepare an individual for immediate action—a phenomenon often referred to as the "fight or flight" response. This survival mechanism, regulated primarily by the autonomic nervous system and the release of hormones such as adrenaline and cortisol, enables people to respond quickly and efficiently to potentially dangerous situations. Historically, this response was critical for early humans in avoiding predators or other physical threats.

However, in today's fast-paced and demanding world, the sources of stress have significantly evolved. Rather than encountering life-threatening scenarios on a regular basis, individuals now face chronic stressors that stem from work-related pressures, academic challenges, financial instability, health concerns, and interpersonal conflicts. These modern-day stressors, while not immediately life-threatening, can still activate the same physiological stress responses as more acute dangers. Over time, repeated or prolonged activation of the stress response system can have detrimental effects on both physical and mental health.

Chronic stress has been closely linked to a wide range of serious health conditions. Prolonged exposure to stress hormones can contribute to the development of cardiovascular disease by increasing blood pressure and causing inflammation in the arteries. Additionally, stress is a major contributor to psychological disorders such as anxiety and depression, which can significantly impair an individual's quality of life and overall functioning. Furthermore, stress has been shown to weaken the immune system, making the body more susceptible to infections and slowing down recovery from illness [1].

Given the pervasive nature of stress in contemporary life, it is increasingly important to understand the biological mechanisms behind it, identify common stressors, and develop effective coping strategies. Recognizing the sources and symptoms of stress can help individuals take proactive steps to manage their stress levels. Techniques such as regular physical exercise, mindfulness meditation, time management, social support, and professional counseling have all been shown to reduce stress and improve well-being. By fostering awareness and implementing healthy coping mechanisms, individuals can mitigate the negative effects of stress and promote a more balanced, resilient, and fulfilling life [1].

This discussion will delve deeper into the various dimensions of stress, including its neurobiological foundations, the external and internal stressors commonly encountered in everyday life, and a range of scientifically supported approaches to stress management. Ultimately, by enhancing our understanding of stress and its far-reaching implications, we can better equip ourselves to navigate the demands of modern living while safeguarding our mental and physical health.

To effectively address the challenges associated with stress, it is becoming increasingly important to shift from reactive approaches to more proactive strategies. One such strategy involves the ability to predict whether an individual is likely to experience stress in the near future. Predictive insights can play a crucial role in helping individuals take preventive measures and adopt timely interventions, thereby reducing the intensity or duration of stress episodes and improving overall well-being [2] [3]. With advancements in data analytics and artificial intelligence, particularly in the field of machine learning, it is now possible to analyze a wide range of behavioral and lifestyle patterns to make informed predictions about future stress levels.

Machine learning algorithms can be trained on data collected from daily activities and behavioral trends to recognize patterns that are indicative of stress. These behaviors include various physical, psychological, and social factors that can serve as predictors of stress. For instance, irregular or insufficient sleep has been widely associated with increased stress levels, as the body and mind require adequate rest to function optimally [4]. Similarly, variations in workout routines—whether excessive physical exertion or complete inactivity—can reflect an individual's coping mechanisms or lack thereof in response to stress [5]. Work habits such as extended working hours, lack of breaks, and increased workload intensity can also be major contributors to chronic stress.

Additionally, screen time has become a significant behavioral indicator in the digital age. Prolonged exposure to screens, whether for work, social media, or entertainment, can impact sleep quality, social interactions, and mental health, often correlating with heightened stress [6] [7]. The quality and frequency of social interactions also offer key insights, as reduced communication or strained relationships may point to underlying emotional or psychological distress [8]. Dietary patterns, including the intake of nutritious versus unhealthy food, frequency of meals, and eating habits, are also closely tied to stress levels [9]. Furthermore, lifestyle choices such as smoking and alcohol consumption can contribute to increased stress levels, making them important variables to consider in stress prediction models. [10].

Recreational activities, while generally beneficial for mental relaxation and emotional well-being, can also provide valuable clues. A lack of engagement in hobbies, entertainment, or leisure pursuits may signal stress or burnout[11] [12]. By integrating and analyzing these diverse data points using sophisticated machine learning techniques, researchers and developers can build predictive models that forecast stress levels with considerable accuracy [13] [14].

Despite the potential of these predictive technologies, a significant limitation remains: many current studies and applications in this domain depend heavily on data obtained from wearable devices such as smartwatches and fitness trackers. These devices often monitor heart rate variability, sleep cycles, physical activity, and more. However, they are not universally accessible due to factors like cost, technological literacy, and personal preference. This reliance on wearables restricts the scalability and inclusiveness of stress prediction systems, especially in low-resource settings or among populations less inclined to adopt wearable technology.

To highlight this issue, Figure 1 illustrates the distribution of users who currently utilize wearable devices like smartwatches. This visualization emphasizes the disparity in access and usage across different demographics and regions, underlining the need for alternative data collection methods that are more accessible and inclusive. Developing models that can function effectively without wearable device data, by leveraging information from smartphones, self-reports, or other non-invasive sources, could greatly expand the reach and impact of predictive stress management tools.

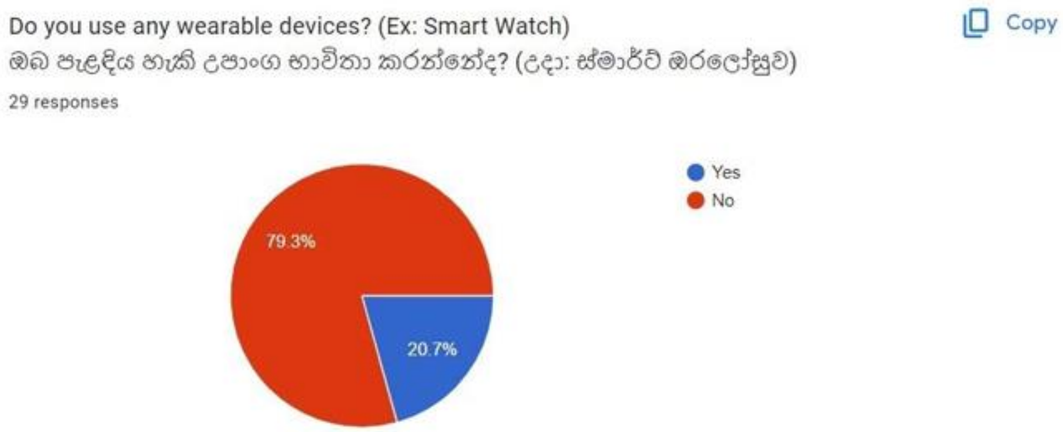

Figure 1 Usage of wearable devices

Our proactive approach to stress management focuses on empowering individuals with the ability to recognize potential stressors in advance and take preventative action before stress escalates to unmanageable levels. By identifying early warning signs and behavioral indicators of stress, individuals are better positioned to make informed lifestyle changes, seek support, and engage in healthy coping mechanisms. This anticipatory strategy represents a significant shift from traditional, reactive methods of stress intervention, which typically address stress only after it has already taken a toll on one's mental or physical health.

The growing interest in mental well-being and self-care has driven people to become more aware of their emotional states and more willing to explore tools that help forecast future stress. This shift reflects a broader cultural change toward holistic wellness and long-term health planning. As awareness grows around the impact of chronic stress on quality of life, productivity, and overall health, individuals are increasingly seeking ways to monitor, predict, and manage their stress proactively.

Figure 2 provides a detailed visualization of the level of interest among individuals regarding the prediction of their future stress levels. The data showcased in this figure highlights a strong and growing desire among people to understand their mental health better, not just in the present moment, but in terms of how it may evolve in the near future. This interest is not limited to specific age groups or professional backgrounds; it spans across students, working professionals, caregivers, and others who face daily pressures that could lead to stress accumulation.

The figure underscores how people place considerable importance on anticipating stress, with many expressing a willingness to adopt tools or applications that help them stay ahead of potential triggers. This proactive mindset is particularly important in environments where stress is continuous or unavoidable, such as high-pressure workplaces or competitive academic settings. By equipping individuals with predictive insights, they can adopt personalized coping strategies—whether that means improving sleep hygiene, setting boundaries at work, engaging in regular exercise, or seeking professional support in advance.

Moreover, this increasing interest in stress forecasting is a promising sign for researchers and developers working on stress detection and prediction technologies. It signals a readiness among the population to integrate such tools into their daily routines, especially if they are accessible, user-friendly, and tailored to individual lifestyles. In turn, this can lead to better health outcomes and reduced reliance on clinical intervention by promoting preventative self-care and mental health maintenance.

In summary, the information presented in Figure 2 reflects not only a growing curiosity but a genuine need for accessible and reliable methods to forecast and manage stress proactively. This insight supports the continued development and deployment of data-driven, personalized stress management solutions that can positively impact the lives of a broad range of individuals.

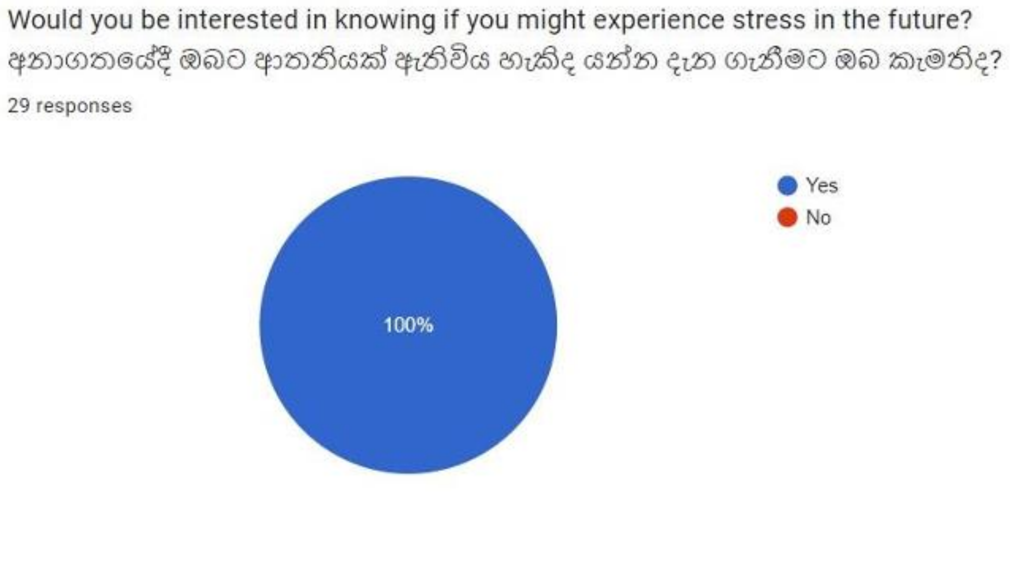

Figure 2 User preference for knowing the future stress

Being able to identify the threat of stress in advance offers significant advantages for users, particularly in terms of convenience and prevention. When individuals are aware that they may be heading toward a period of heightened stress, they can take deliberate steps to mitigate its impact before it becomes overwhelming or detrimental to their well-being. Early recognition empowers users to implement lifestyle adjustments, engage in relaxation techniques, or seek emotional support, all of which can significantly reduce the severity and duration of stress episodes. This approach not only enhances individual resilience but also promotes a healthier, more balanced lifestyle.

To support this proactive approach, we go a step further by offering personalized activity plans that are specifically tailored to each user's unique profile. These customized plans are generated based on multiple factors, including the user's current stress level, age, lifestyle, daily routines, and the amount of free time they have available. By considering these variables, the plans ensure that the recommended activities are not only effective but also realistic and easy to incorporate into everyday life. This level of personalization maximizes the likelihood that users will follow through with the recommendations, ultimately supporting long-term mental health maintenance.

In addition to proactive planning, we are also developing a chatbot-based support system designed to assist users in real-time when they are experiencing stress. While speaking to a real person—such as a friend, family member, or mental health professional—can be incredibly beneficial, not everyone has immediate access to such support. Some individuals may feel isolated, while others might hesitate to open up due to concerns about judgment, privacy, or vulnerability. The chatbot serves as an accessible, non-judgmental alternative that users can turn to at any time of day. It offers a safe space for users to express their thoughts, receive empathy, and access stress-relief strategies, all while maintaining complete confidentiality.

The chatbot is designed to simulate human-like conversation, offering empathetic responses and guiding users through calming activities. Over time, it can also learn from user interactions, improving its ability to offer relevant support and personalized advice. This makes it a valuable tool for moments when human interaction isn't possible or comfortable. It also complements the other tools in our stress management ecosystem by offering on-demand emotional assistance.

To better understand how individuals prefer to seek support when dealing with stress, Figure 3 presents a comprehensive overview of users' coping preferences. It illustrates the diverse range of methods that people turn to in times of emotional distress—ranging from face-to-face communication and professional therapy to digital tools such as mobile apps, self-help resources, and chatbots. The figure reveals important insights into user behavior, such as the increasing comfort with technology-assisted emotional support, the reliance on anonymity in mental health conversations, and the value placed on immediate access to guidance. These insights help inform the development of tools that meet users where they are, both emotionally and technologically.

As we've seen, our approach combines early detection, personalized intervention, and accessible emotional support to create a holistic system for stress management. By understanding how users prefer to engage with support tools, and by offering both proactive and reactive solutions, we aim to provide a comprehensive framework that empowers individuals to take control of their mental health in ways that feel safe, comfortable, and effective.

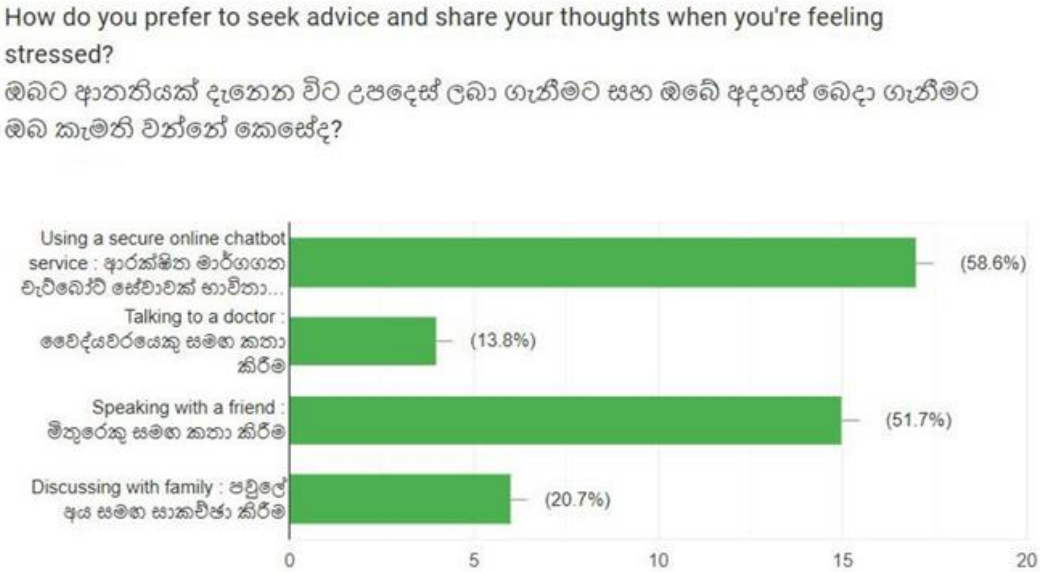

Figure 3 User preference for seek advice and sharing thoughts when feel stressed

In conclusion, stress is a multifaceted and pervasive issue that affects nearly every aspect of modern life, from personal health and relationships to work performance and overall well-being. It arises from a wide range of sources—both internal and external—and manifests in numerous ways, influencing individuals at different points in their lives. As a natural physiological response to challenges or demands, stress is not inherently harmful; however, when it becomes chronic or unmanaged, it can lead to significant physical, emotional, and psychological health problems. Understanding the causes and effects of stress, as well as its intricate biological and psychological underpinnings, is the first step toward managing it effectively [1].

With the rapid advancements in technology, particularly in the fields of machine learning and data analytics, we now have the ability to predict potential stress events before they escalate. Through the analysis of behavioral patterns such as sleep, exercise, diet, work habits, and social interactions, machine learning models can detect early warning signs of stress, enabling individuals to take proactive measures. This predictive capability allows for tailored interventions that are both timely and personalized, ensuring that individuals can better manage their stress levels before they reach a critical point [13] [14]. By leveraging this technology, we can shift the focus from reactive to proactive stress management, empowering people to take control of their mental health and prevent stress from becoming overwhelming.

In addition to predictive tools, personalized activity plans offer another key solution for managing stress. These plans, which are custom-designed to suit each individual's specific needs, preferences, and lifestyle, provide practical and sustainable strategies for reducing stress. Whether it's through regular physical activity, mindfulness exercises, or time management techniques, personalized activity plans take into account the user's unique circumstances—such as their available time, stress levels, age, and personal goals—ensuring that the recommendations are both achievable and effective. This level of personalization increases the likelihood that individuals will adopt these strategies, ultimately helping them develop healthy habits that mitigate stress over the long term.

Furthermore, the development of supportive technologies like chatbots provides a valuable resource for individuals who may not have access to traditional forms of support, such as face-to-face therapy or guidance from friends and family. Chatbots offer a confidential, non-judgmental, and easily accessible means for individuals to express their feelings, receive emotional support, and access coping strategies in real time. While a real person's support is often beneficial, not everyone has someone to turn to, and for some, discussing personal issues with others can feel uncomfortable or intimidating. Chatbots offer a much-needed alternative, providing immediate assistance without the emotional barrier that may accompany human interaction. By integrating these technologies into stress management systems, we provide individuals with an additional tool to cope with stress and promote mental well-being in an accessible and user-friendly way.

Ultimately, the strategies outlined above—predictive stress analytics, personalized activity plans, and supportive technologies—work together to create a comprehensive approach to managing stress. These solutions empower individuals to take charge of their mental health, offering resources and strategies that are both practical and effective. By fostering a more proactive and holistic approach to stress management, we not only enhance individual well-being but also contribute to the development of a more resilient, healthier, and productive society. Reducing stress at the individual level has far-reaching benefits, including improved physical health, better interpersonal relationships, and enhanced workplace productivity, all of which contribute to a higher quality of life for individuals and communities alike.

In summary, addressing stress effectively is not just about managing the symptoms but about taking a comprehensive, preventative approach that equips individuals with the tools and knowledge they need to navigate the challenges of modern life. By combining cutting-edge technology with personalized support, we can empower individuals to thrive in an increasingly demanding world, ultimately leading to healthier, happier lives for all.

1.2.Literature Review

In the domain of stress management and prediction, a growing body of research focuses on understanding and mitigating the effects of stress through various methodologies. As we explore this literature review, it becomes evident that significant strides have been made in the identification of stressors and the development of coping strategies. A thorough examination of research papers reveals several key areas of focus, including the impact of lifestyle factors on stress and the application of machine learning techniques for stress prediction.

I have studied numerous research papers on stressors such as sleep patterns, physical activity, work habits, and social interactions, as well as the use of machine learning for predicting stress. [13] While there is a substantial amount of research demonstrating the connection between these behaviors and stress, there is a notable gap in research specifically focused on predicting future stress based on a combination of behavioral patterns. Most existing studies on stress prediction rely on wearable devices like smartwatches, which are not universally accessible.

This highlights the need for more comprehensive and accessible approaches to predicting stress without the necessity of specialized equipment. The current literature underscores the importance of further exploration in this area to develop more inclusive and practical methods for proactive stress management.

A pivotal study published in the Journal of Medical Internet Research highlighted the potential of consumer wearables in predicting changes in mental health measures such as stress. [15] This study, part of the LEMURS, involved students from a public university who provided continuous biometric data and weekly surveys during their first semester. Through mixed-effects regression models, the study identified consistent associations between perceived stress scores and sleep metrics. For instance, an additional hour of TST decreased the odds of moderate-to-high stress by 38.3%, while a 1 beat per minute increase in RHR increased these odds by 3.6%. These findings persisted after controlling gender and week of the semester, highlighting the role of sleep data in predicting stress and addressing mental health challenges among college students.

Another significant contribution to the field is a study published in Nature which investigated the use of machine learning models to predict future stress levels based on various behavioral and physiological data. [14] This research demonstrated that incorporating data from wearable devices, such as heart rate variability and sleep patterns, significantly improved the accuracy of stress predictions. By analyzing these data points, the study was able to identify individuals at risk of experiencing high stress levels in the near future, allowing for timely interventions and stress management strategies.

In addition, a study presented at the IEEE International Conference on Healthcare Informatics explored the use of physiological and behavioral data to predict stress in real-time using advanced machine learning algorithms. [3] The research utilized a combination of heart rate, skin conductance, and activity level data to build predictive models. The results showed that integrating multiple data sources improved the model's accuracy in predicting future stress.

Sleep deprivation has been linked to increased vulnerability to acute psychosocial stress in both young and older adults. Research indicates that lack of sleep exacerbates stress responses, making individuals more susceptible to stress-related health issues. [4] This connection highlights the importance of adequate sleep in managing stress and suggests that sleep patterns can be a valuable predictor of future stress levels. Physical activity is another critical factor in stress management. Studies have shown that regular exercise can reduce stress and improve overall well-being. For example, research conducted in Madrid analyzed the relationship between exercise frequency and stress reduction in working professionals [5], finding a significant correlation between regular physical activity and lower stress levels. Diet also plays a crucial role in stress management. High-fat diets have been found to induce changes in neuronal function linked to redox stress, with differential effects based on age and gender. [9] This suggests that dietary habits can influence stress levels and should be considered when predicting future stress. Social interactions and recreational activities significantly influence stress levels. Engaging in shared activities has been identified as a protective factor against behavioral and psychological symptoms of stress. Research involving university students in Finland revealed that clusters of lifestyle behavioral risk factors, including the quality of social interactions, were associated with depressive symptoms and increased stress [16]. Additionally, screen time has emerged as a critical factor in stress research. Studies, such as those conducted during the COVID-19 pandemic among students at the University of Peradeniya [6], have shown that increased screen time is linked to higher stress levels. Excessive use of digital devices during this period has been associated with heightened stress and mental health issues among both students and teachers.

Recent studies have also highlighted the impact of recreational activities and lifestyle behaviors on stress management. A study on adult women found that engaging in regular recreational activities significantly reduces stress levels while enhancing happiness and life satisfaction [12]. Similarly, research on adolescents has revealed a concerning link between stress perception and unhealthy behaviors such as smoking and drinking, underscoring the importance of addressing these behaviors in stress management strategies [10]. These findings emphasize the need for holistic approaches that consider both recreational and lifestyle factors in predicting and managing stress.

In conclusion, the literature on predicting stress and understanding its behavioral correlations provides significant insights into the potential of various technologies and methodologies. Wearable devices have shown promise in measuring sleep and predicting mental health changes, with consistent associations between sleep metrics and perceived stress. Machine learning models further enhance the accuracy of stress prediction by integrating diverse physiological and behavioral data. Despite these advancements, there is a notable gap in research specifically focused on predicting future stress without reliance on wearable devices. Addressing this gap could lead to more accessible and comprehensive stress management solutions, ultimately improving individual well-being and mental health outcomes.

1.3.Research Gap

The research papers reviewed over the past few weeks highlight a significant gap in the prediction of future stress using non-invasive, accessible methods. While much of the current research connects behavioral patterns like sleep, exercise, work habits, and screen time to stress levels, there is a clear lack of studies focused on predicting future stress without relying on wearable devices like smartwatches. These devices, while effective, are not universally accessible, limiting the applicability of existing models.

Although wearables track factors such as heart rate, sleep, and physical activity, their cost, technological complexity, and need for continuous user engagement make them impractical for many people. This limits the reach of predictive models based on wearables, as they exclude individuals in low-resource settings or those who cannot afford or choose not to use such devices. Additionally, wearables often require a level of technological fluency that may not be accessible to everyone, further hindering widespread adoption.

Given these limitations, there is an urgent need for research to explore alternative, more inclusive methods of predicting stress. Smartphones, which are widely available and used by a large portion of the population, could provide a viable alternative. These devices can collect behavioral data through apps, sensors, and self-reported surveys, offering a more accessible solution for stress prediction.

At this stage, while wearables have made valuable contributions to stress research, their limitations call for the development of non-invasive, universally accessible methods. This shift could provide a more inclusive and effective approach to predicting and managing stress, reaching a broader demographic and ensuring that stress management tools are available to everyone.

Furthermore, while machine learning models have proven effective in predicting stress, the majority of existing research relies heavily on biometric data—such as heart rate, sleep patterns, and physical activity. While these metrics undoubtedly provide valuable insights into current stress levels, this approach tends to overlook the vast potential of integrating a wider range of behavioral data, such as work habits, social interactions, and daily routines. By relying predominantly on biometric data, current models miss an opportunity to create a more holistic understanding of stress that considers the broader spectrum of behavioral factors influencing an individual's stress experience. This oversight underscores a critical gap in the current body of research, highlighting the need for novel, inclusive methodologies that can leverage the readily available behavioral data we encounter in our daily lives.

The proposed system seeks to address this knowledge gap by offering a creative and innovative solution that goes beyond the limitations of existing methods. By utilizing a mobile-based platform, the system employs advanced machine learning techniques to analyze and predict future stress based on diverse behavioral patterns. Unlike traditional approaches, this system bypasses the need for specialized wearable devices, which often come with accessibility and cost barriers, making it much more accessible to a broader audience. The platform capitalizes on the ubiquity of smartphones—devices that are increasingly part of our daily lives—and utilizes self-reported data to collect relevant behavioral data that can help forecast stress.

In addition to predicting stress, the system enhances its practical utility by incorporating personalized activity recommendations tailored to individual stress profiles. These recommendations take into account an individual's daily routine, lifestyle choices, and current stress levels, offering actionable suggestions for stress management that are both accessible and easy to implement. Moreover, the platform includes a confidential chatbot feature that provides real-time support, offering users a safe space to express their concerns and receive advice on managing their stress. This feature is particularly valuable, as it ensures that users have access to immediate assistance and guidance, promoting timely interventions that can prevent stress from escalating.

Table 2 provides a clear comparison between this proposed system and existing solutions, highlighting how it uniquely addresses the gaps in current stress prediction models. It demonstrates the system’s innovative features, such as its use of accessible mobile technology, its integration of diverse behavioral data, and its emphasis on personalized, actionable recommendations. By offering these advanced capabilities, the proposed system represents a significant improvement over existing methods, promising to make stress prediction and management more inclusive, personalized, and effective for a wider range of individuals.

In summary, this mobile-based system represents a paradigm shift in how we approach stress prediction and management. By moving beyond the reliance on wearable devices and incorporating a broader range of behavioral data, it opens the door to more inclusive, accessible, and personalized stress management solutions. This approach not only addresses the current limitations of existing research but also paves the way for more scalable and practical stress prediction tools that can ultimately improve the well-being of individuals across different demographics.

	Our Proposed Solution	Stress and Sleep Monitoring with Wearable devices	ML for Predicting Stress	Biometric Data for Stress Prediction	Headspace	Calm	My Fitness Pal
Mobile App	✓	✗	✗	✗	✓	✓	✓
Predict Stress in the Future	✓	✓	✓	✓	✗	✗	✗
Has a Chatbot	✓	✗	✗	✗	✓	✓	✗
Recommend Activity Plans	✓	✗	✗	✗	✗	✓	✓
Use Machine Learning	✓	✓	✓	✓	✓	✓	✓
No Wearable Devices	✓	✗	✗	✗	✓	✓	✓
Behavioral Analysis	✓	✗	✗	✗	✗	✓	✗

Figure 4.Research Gap

1.4.Research Problem

The research problem addressed in this study stems from the ongoing challenge of predicting and managing stress effectively, despite the increasing recognition of its negative impact on both mental and physical health. Stress is a pervasive issue in modern life, affecting individuals across various demographics and contexts. Although significant progress has been made in understanding the physiological and psychological effects of stress, current systems designed to assess and manage stress remain limited in their effectiveness. Traditional stress management methods often rely on wearable devices such as smartwatches and fitness trackers to measure physiological data like heart rate, sleep patterns, and physical activity levels. While these devices have proven useful for tracking real-time data, they present notable limitations, particularly in terms of accessibility, cost, and the need for constant user engagement.

A major challenge with wearable-based stress management systems is their lack of inclusivity. Wearable devices are not universally available or affordable, and many individuals, particularly those in low-resource settings, may not have access to these technologies. Additionally, these devices often require continuous monitoring and user engagement, which can be burdensome or impractical for some individuals. Moreover, while these devices collect valuable biometric data, they do not offer a comprehensive solution that integrates both predictive analytics and personalized support to address stress in a proactive and timely manner.

Furthermore, current systems in the stress management domain often fail to provide comprehensive solutions that integrate predictive analytics with personalized and confidential support. Many existing models focus exclusively on detecting stress after it has occurred, relying on observable physical cues and biometrics. However, these systems typically lack the capability to offer real-time interventions or customized guidance that would allow users to take timely actions to manage their stress. In particular, there is a notable gap in mobile-based systems that could provide users with immediate, personalized feedback and support, without relying on costly or complex wearable devices.

This research seeks to explore how advanced machine learning techniques can be leveraged to address these gaps and develop a novel, mobile-based solution for stress management. By analyzing diverse behavioral patterns—including sleep, exercise, work habits, screen time, and social interactions—the proposed system aims to predict future stress levels with greater accuracy. This predictive approach would allow users to identify stressors before they escalate, empowering them to take proactive steps to manage their stress. Furthermore, the system would integrate personalized activity recommendations, offering users actionable strategies that are tailored to their unique needs, lifestyle, and stress profile. These recommendations would provide guidance on how to reduce stress, improve overall well-being, and promote healthier behaviors.

Additionally, the proposed system would incorporate a confidential chatbot feature, providing users with a safe, anonymous space to express their concerns, receive emotional support, and obtain practical advice on managing their stress. This feature aims to address the emotional aspect of stress management by offering real-time, human-like support without requiring face-to-face interaction. The confidentiality of the chatbot ensures that users can access the help they need without fear of judgment or exposure, which is particularly important for individuals who may hesitate to seek help in more traditional settings.

By combining these elements—predictive analytics, personalized recommendations, and confidential support—this research aims to create a comprehensive solution that goes beyond the limitations of existing stress management systems. The proposed mobile-based platform would make stress prediction and management more accessible, offering users a valuable tool to proactively address their stress in a way that is both convenient and effective. This solution would bridge the current gap in the available technologies by providing an inclusive, cost-effective, and scalable method for stress management that does not rely on wearable devices.

In summary, this study seeks to address the pressing need for a more accessible and effective stress management system, one that integrates predictive analytics, personalized interventions, and real-time support. By exploring how machine learning techniques can be applied to behavioral data, this research aspires to offer a solution that empowers individuals to manage their stress in a proactive and personalized manner, ultimately improving their mental and physical well-being.

1.5.Research Objectives

The main objective of developing our mobile-based stress prediction and management system is to leverage advanced machine learning techniques to analyze behavioral patterns for predicting the likelihood of a person experiencing stress in the future. This system aims to provide personalized activity recommendations tailored to individual needs and offer support through an integrated chatbot, all without relying on wearable devices.

1.5.1.General Objective

To develop an innovative system that predicts the likelihood of future stress based on individuals' daily behaviors such as sleep, exercise, diet, screen time, and social interactions. The system will assess these behaviors and recommend personalized behavioral changes to help users reduce the risk of stress. Additionally, a chatbot will be available for users to interact with whenever they are feeling stressed, providing immediate support and guidance.

1.5.2.Specific Objectives

1) Behavioral Data Collection and Preprocessing:

   Collect a diverse set of behavioral data, including sleep patterns, workout routines, work habits, screen time, social interaction quality, diet, smoking and drinking habits, and recreational activities and preprocess them.

2) Development of Stress Prediction Model:

   Design and implement a machine learning model to analyze behavioral patterns in order to predict whether an individual is likely to experience stress in the near future.

3) Personalized Activity Recommendations:

   Develop algorithms to generate personalized activity plans based on the user's stress level, age, available time, and other relevant factors.

4) Chatbot Integration for Stress Support:

   Integrate a chatbot into the mobile application to provide users with accessible and confidential support for stress management.

5) System Integration and Mobile App Development:

   Integrate the stress prediction model, personalized activity recommendation algorithms, and chatbot into a user-friendly mobile application.

6) Evaluation and Validation:

   Conduct comprehensive testing and validation of the mobile application to ensure accuracy, usability, and effectiveness in predicting stress and providing support.

2.Methodology

Figure 2 provides a comprehensive overview of the stress prediction system as integrated into the AyurAura mobile application. This subsystem is designed to help users anticipate potential stress before it becomes critical, empowering them to take preventive actions. The system begins by collecting behavioral input from users, which include parameters such as sleep patterns, dietary habits, physical activity levels, work routines, social interactions, and digital device usage etc. This data serves as a foundational input for the machine learning model.

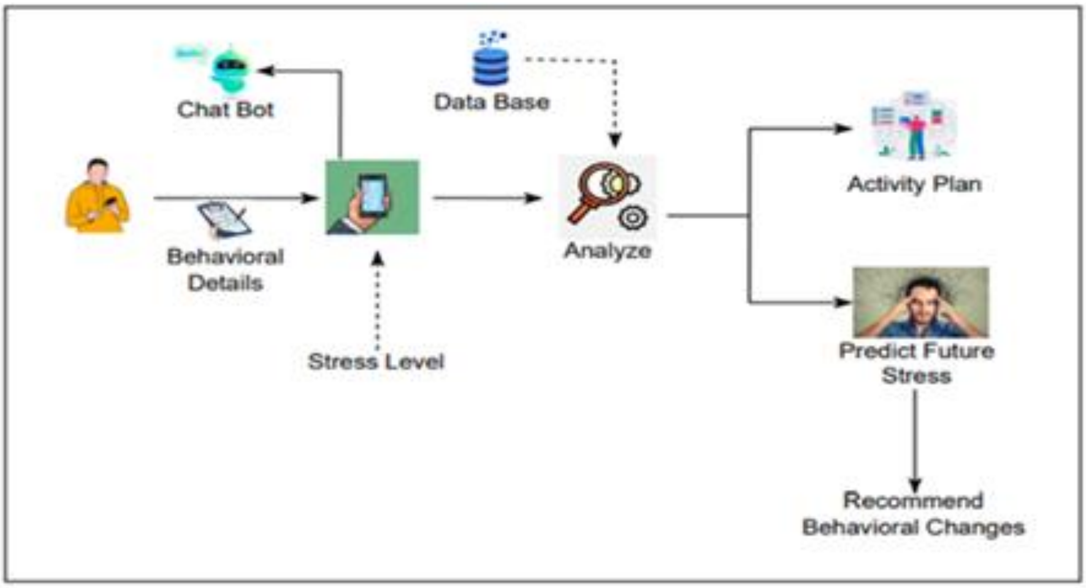

Figure 5. Prediction of future stress likelihood flow.

To process this behavioral data, the system utilizes a Random Forest classifier, a robust and interpretable machine learning algorithm known for its high accuracy and resistance to overfitting. The Random Forest model is trained on a dataset that includes a diverse range of behavioral profiles labeled with corresponding stress likelihood, allowing it to learn patterns that signal the early onset of stress. When users submit their current behavioral data, the model analyzes these inputs in real time to predict the likelihood of future stress. This prediction is then presented to the user in an easily understandable format.

For users who are identified as being at moderate to high risk of experiencing stress, the system offers immediate, personalized recommendations for behavioral modification. These suggestions are based on evidence-driven wellness strategies and may include tips such as increasing physical activity, adjusting sleep routines, or reducing screen time. The goal is to enable users to adopt healthy habits early enough to prevent the escalation of stress.

In addition to predictive analytics, the AyurAura app features a motivational chatbot, which acts as a supportive companion for users experiencing emotional discomfort. This chatbot is powered by langflow and fine-tuned specifically for empathetic and contextually aware conversations related to stress and mental health. The chatbot can understand natural language inputs and respond in a thoughtful and human-like manner. Users can initiate conversations with the chatbot at any time, whether they need to vent, seek advice, or request calming exercises.

Together, the stress prediction system and the motivational chatbot form a dynamic and adaptive support framework within AyurAura. While the machine learning model enables users to stay ahead of stress by predicting and preventing it, the chatbot ensures that emotional assistance is always available when users need it most. This synergistic integration not only improves the app's effectiveness but also enhances user trust and engagement, fostering a more proactive and sustained approach to mental wellness and self-care.

Data collection for stress prediction model was carried out using a comprehensive survey-based approach, targeting a diverse group of 1,000 participants. This data was gathered through both Google Forms and in-person surveys, ensuring a broad demographic representation and improving the reliability of the results. The survey was carefully designed to capture a wide array of behavioral variables that are commonly associated with stress, with questions framed to ensure clarity and consistency across responses.

The key behavioral determinants identified and recorded included sleeping habits (average hours of sleep per night), the frequency and intensity of physical exercise, and working hours per day or week, which included both professional commitments and academic responsibilities. Screen time (time spent on mobile phones, computers, and television)—was also tracked, as extended exposure to screens has been linked to cognitive fatigue and increased stress.

Participants were also asked to report on their dietary habits. Another important category in the data collection was substance use, particularly the frequency of smoking and alcohol consumption, as both behaviors are known to correlate with elevated stress levels in the short and long term. Lastly, the survey examined each participant's engagement in leisure and recreational activities, such as hobbies, socializing, creative pursuits, or relaxation practices, as these have a significant impact on emotional well-being and resilience against stress.

By collecting information across these multiple behavioral dimensions, the dataset provides a rich foundation for training the Random Forest-based stress prediction model. The diversity of the participant pool and the range of lifestyle factors considered ensure that the model can generalize well across different user profiles, enabling more accurate and personal predictions of stress likelihood in real-world scenarios.

After the data collection phase was successfully completed, a licensed medical professional was consulted to evaluate and categorize the responses. Based on the behavioral data submitted by the 1,000 participants, the doctor carefully classified individuals into two distinct groups: those who are likely to experience stress and those who are unlikely to be at risk. This classification was grounded in clinical expertise and aligned with widely accepted diagnostic indicators and behavioral risk factors associated with stress.

The categorization process was not arbitrary; instead, it was systematic and evidence-informed, relying on the analysis of key behavioral patterns known to contribute to stress. For instance, irregular or insufficient sleep, prolonged working hours, insufficient engagement in regular physical exercise, poor diet, substance use, excessive screen time, and limited engagement in leisure activities are all well-documented contributors to heightened stress levels. Participants who showed a clustering of such behaviors were flagged as having a higher probability of experiencing stress, while those maintaining balanced and healthy daily routines were placed in the lower-risk category.

The result was a labeled dataset that not only reflected real-world behavioral tendencies but also incorporated expert medical judgment, thereby making it highly suitable for training a machine learning model to predict future stress with increased accuracy.

Moreover, using a clinician-labeled dataset ensures that the prediction model is grounded in human expertise, lending credibility to the predictions made by the system once deployed. This approach bridges the gap between clinical insights and computational methods, strengthening the practical applicability of the stress prediction system in everyday mental wellness monitoring.

This categorization, established by the medical professional, became the target variable for training the machine learning model. The process of labeling individuals as either likely to experience stress or not allowed the model to learn patterns within the behavioral data that correlate with stress susceptibility. With this classification in hand, the dataset became more than just a collection of raw information—it transformed into a supervised learning dataset that could guide the machine learning algorithm in predicting future stress likelihood. By using this clear-cut target variable, the system can make informed predictions based on historical behavioral patterns, allowing it to recognize stress-inducing behaviors and assess their potential long-term effects on an individual's mental health.

The dataset was diverse and contained a wide variety of behavioral profiles, which was crucial for extracting significant conclusions related to stress prediction. These varied behavioral patterns provided the necessary richness for the machine learning model to differentiate between high-risk and low-risk individuals with accuracy. The inclusion of a range of factors such as sleep quality, exercise frequency, working hours, substance use, and leisure activities allowed the model to not only identify stress triggers but also to pinpoint which combination of factors was most strongly linked to heightened stress levels. This type of comprehensive data set allowed the model to perform a detailed multivariable analysis, taking into account multiple behavioral determinants simultaneously.

Despite the strong foundation laid by the 1,000 participants, there are inherent limitations to the dataset. While 1,000 individuals form a solid sample size for initial development, there is room for improvement in terms of demographic diversity. The current dataset may not fully represent the broad spectrum of the population, including variations in age, gender, cultural background, socioeconomic status, or geographic location. For example, individuals in certain regions or communities may experience stress differently due to cultural norms, lifestyle habits, or access to mental health resources. Additionally, certain age groups may exhibit different stress predictors based on life stage or generational behavior patterns.

Expanding the dataset to include a more diverse sample from various demographic backgrounds would likely enhance the model's ability to generalize across different user profiles. By incorporating participants from a wider range of socioeconomic, cultural, and geographical contexts, the model would have access to a broader array of behavioral patterns, thus improving its predictive accuracy for diverse populations. With this broader data, the model could be fine-tuned to account for variations in stress triggers across different life circumstances, improving its reliability and robustness when deployed in real-world settings.

Furthermore, an increased dataset size would provide the opportunity for more fine-grained analysis of different stressors and their impacts on various subgroups. The inclusion of additional participants would also increase the statistical power of the model, ensuring that the patterns learned are not merely coincidental but reflect true, underlying relationships between behaviors and stress levels.

During the data preprocessing phase, several crucial steps were taken to ensure the integrity, consistency, and usability of the dataset. One of the first actions involved addressing the issue of missing data. Rows with incomplete information were identified and removed to maintain the quality of the dataset. Missing data can introduce significant bias and affect the accuracy of the machine learning model, so eliminating rows with absent or incomplete values helped to ensure that only complete records were used for analysis. This step helped in minimizing any potential distortions that could arise from inconsistencies in the dataset, thus enhancing the reliability of the model's predictions.

In addition to handling missing data, duplicate values were systematically identified and removed. Duplicates can occur during data collection or entry and, if left unchecked, could lead to data redundancy, causing certain observations to be overrepresented in the model. This redundancy could distort the machine learning algorithm's learning process, especially in models like Random Forest, where overrepresented data points may bias the results. By eliminating duplicates, we ensured that each observation in the dataset was unique, allowing the model to process a diverse set of data points without bias from repeated entries.

To further improve the readability and usability of the dataset, column names were also renamed for better clarity. In many raw datasets, column names can be cryptic or overly technical, which can hinder comprehension and make data analysis more cumbersome. By renaming columns to be more descriptive and intuitive, we made the dataset easier to navigate, reducing the chances of confusion and error during analysis. Clear column names also help in facilitating easier interpretation of the results, especially when collaborating with other team members.

Another important preprocessing step involved standardizing numerical features in the dataset. Since the dataset contained a mix of numerical values that varied in scale—such as the number of hours of sleep, amount of screen time, and frequency of exercise—standardization was applied to bring all numerical features onto the same scale. Without standardization, features with larger numerical values (such as working hours) could dominate the model's learning process, while features with smaller numerical values (like sleep hours) could be overlooked. By scaling the features to a consistent range, we ensured that each feature contributed equally to the model's predictions, allowing for more balanced and effective learning. This step was particularly crucial for models like Random Forest, which rely on the relative importance of each feature for making accurate predictions.

These preprocessing step-dropping rows with missing data, removing duplicates, renaming columns, and standardizing numerical features—played a pivotal role in purifying the dataset. By addressing potential issues early in the data preparation process, we ensured that the data was clean, structured, and ready for model training. This careful attention to data quality significantly optimized the performance of the machine learning model, helping it learn more effectively and produce more reliable predictions when deployed in real-world stress management scenarios.

Pseudocode for Stress Likelihood Prediction Model

Input: Behavioral data. (sleep, exercise, work hours, screen time, social interaction quality, healthiness of diet, drinking and smoking, recreational activities)

Output: Predicted likelihood of stress (Stress / No Stress).

BEGIN

1. Import necessary libraries (e.g., pandas, sklearn, RandomForestClassifier, joblib, seaborn, matplotlibt).
2. Load the dataset containing behavioral data and stress probability.
3. Preprocess the data:
    - Remove incomplete data rows.
    - Rename column names for better readability.
    - Remove duplicate rows.
4. Define the target variable (stress_probability).
5. Split the dataset into training (80%) and testing (20%) sets.
6. Initialize a Random Forest Regressor/ KNN Classifier.
7. Train the model using the training data.
8. Evaluate the model:
    - Predict stress probability on the test data.
    - Calculate accuracy, classification report, and confusion matrix.
9. Save the trained model and scaler for future use.
10. Output predicted stress probability

END

The Stress Likelihood Prediction Model begins by importing the necessary libraries that are essential for data processing, machine learning model training, and evaluation. Libraries such as pandas are used for data manipulation, sklearn provides machine learning algorithms and evaluation tools, joblib is utilized for saving the trained model for future use, and matplotlib and seaborn are used for data visualization. These libraries are fundamental to building, training, and assessing the performance of the model.

Once the libraries are imported, the next step is to load the dataset. This dataset contains various behavioral features, such as sleep patterns, exercise frequency, working hours, screen time, the quality of social interactions, healthiness of diet, smoking and drinking habits, and participation in recreational activities. These behavioral attributes are the key inputs for the model, which aims to predict the likelihood of stress based on these factors.

After loading the dataset, the preprocessing phase begins to ensure that the data is clean and ready for analysis. Incomplete data rows, which may have missing values, are removed to prevent the model from being trained on inaccurate or inconsistent data. Additionally, column names are renamed to more readable and descriptive terms, making it easier to understand the dataset’s structure. The preprocessing step also involves identifying and eliminating any duplicate rows, ensuring that the model is not biased by redundant data entries. These preprocessing tasks are crucial in maintaining the integrity and quality of the dataset.

Once the data is preprocessed, the target variable for the model is defined. In this case, the target variable is the stress_probability, which indicates the likelihood of an individual experiencing stress. This variable is categorized as either Stress or No Stress, depending on the individual’s behavioral data. The machine learning model is trained to predict this target variable based on the input features.

To evaluate the model's performance, the dataset is split into training and testing sets. Typically, 80% of the data is used for training the model, and the remaining 20% is reserved for testing. This division ensures that the model can learn from a large portion of the data while also being evaluated on unseen data to gauge its generalizability and accuracy.

Next, the model is initialized using a suitable machine learning algorithm, such as a Random Forest Regressor or KNN Classifier. These algorithms are selected because they are capable of handling complex datasets and can provide accurate predictions. The model is then trained using training data, during which it learns the relationships between the input behavioral features and the target variable, stress probability. This training process allows the model to optimize its internal parameters to make the most accurate predictions.

Once the model is trained, it undergoes an evaluation phase where its performance is tested using the testing data. During evaluation, the model predicts the likelihood of stress for the test set individuals. Key performance metrics such as accuracy are calculated, providing a general measure of how well the model is performing. Additionally, a classification report is generated, which includes metrics like precision, recall, and F1 score to offer a deeper understanding of the model's effectiveness across different categories. The confusion matrix is also used to visualize the model's true positives, false positives, true negatives, and false negatives, giving a clear picture of how well the model distinguishes between stress and no stress cases.

Once the model has been evaluated and refined, it is saved for future use. Using joblib, the trained model and the scaler (used for standardizing numerical features) are saved, allowing for easy deployment without needing to retrain the model each time. This step ensures that the model can be used for making predictions on new, unseen data.

Finally, the model outputs the predicted stress probability for new individuals based on their behavioral data. This prediction helps identify individuals who are at high risk of experiencing stress, allowing for early intervention and personalized support to manage and mitigate stress effectively.

2.1.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 AI-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.

2.2.Testing

The overall performance of the application was evaluated through rigorous testing across all four core components of the powered stress management solution. Each component was tested individually as well as in an integrated environment to ensure reliability, consistency, and alignment with expected outcomes.

This component predicts future stress based on behavioral data input by the user. Additionally, there is a chatbot to help users manage their stress.

Test Case ID	Scenario	Input	Expected Output	Status
4	Validate if the model predicts future stress	Behavioral data	Predict stress likelihood(Stress or no stress).	Pass
5	Ensure the chatbot processes and responds to stress-related queries correctly	"I feel overwhelmed today"	Response: "Would you like to try a calming activity?"	Pass
6	Recommend behavior changes for users to stary stress free if they are likely to be stressed.	Behavioral data	Behavior modification recommendations	Pass

Table 1Test plan of Future Stress Prediction and Chatbot Integration

3.Results & Discussion

The performance of the model was thoroughly evaluated to determine how effectively it can predict stress likelihood based on various behavioral patterns. The evaluation metrics used included accuracy, a classification report, and the confusion matrix, all of which offered different perspectives on the model's ability to make accurate and reliable predictions.

Accuracy is one of the primary metrics used to assess how well the model performs overall. It is calculated by comparing the number of correct predictions (both stress and no-stress) against the total number of predictions made. In the context of stress prediction, accuracy provides an overall measure of how many individuals were correctly classified into their respective categories (stress or no stress). A higher accuracy value signifies that the model is effectively distinguishing between individuals who are likely to experience stress and those who are not. However, it is important to note that accuracy alone does not provide a complete picture, especially when the data may have imbalanced classes (e.g., more people not experiencing stress than those who are).

The classification report delves deeper into the performance of the model by providing additional metrics that give a more granular view of its predictive power. Key metrics such as precision, recall, and F1-score are part of the classification report, which evaluates the model's performance for both the stress and no-stress classes.

Precision is a metric that helps answer the question: Of all the individuals predicted to be experiencing stress, how many actually are? In other words, precision measures the accuracy of the positive predictions (stress). High precision means that the model is good at avoiding false positives (predicting stress when the individual is actually stress-free).

Recall, on the other hand, examines how well the model identifies all individuals who are truly experiencing stress. It answers the question: Of all the individuals who are actually stressed, how many did the model correctly identify? High recall indicates that the model is good at capturing most of the people who are likely to experience stress, minimizing false negatives (missing individuals who should have been flagged as at risk for stress).

The F1-score provides a balance between precision and recall, combining them into a single score that takes both false positives and false negatives into account. It is particularly useful when dealing with imbalanced datasets where one class (stress or no-stress) is much larger than the other.

Lastly, the confusion matrix offers a visual representation of the model's performance. This matrix displays the number of true positives (individuals correctly identified as likely to experience stress), true negatives (individuals correctly identified as not likely to experience stress), false positives (individuals incorrectly identified as stressed when they are not), and false negatives (individuals incorrectly identified as stress-free when they are actually stressed). The confusion matrix is a crucial tool for identifying areas where the model is making mistakes. For example, if there are many false positives, it may indicate that the model is over-predicting stress, while a high number of false negatives may suggest that the model is missing individuals who are actually at risk.

The confusion matrix can also be used to calculate other important evaluation metrics such as specificity and sensitivity, which provide more insight into how well the model is performing in identifying stress and no-stress individuals. Specificity measures the proportion of true negatives among all individuals who are not stressed, while sensitivity (another term for recall) measures how well the model identifies individuals who are actually stressed.

Overall, these performance metrics—accuracy, classification report (precision, recall, and F1-score), and confusion matrix—collectively provide a comprehensive evaluation of the stress prediction model. They help in understanding both the strengths and weaknesses of the model, enabling further improvements and refinements in future iterations. By regularly reviewing these metrics and making necessary adjustments, the model can be continuously enhanced to provide more accurate and reliable stress predictions.

The Random Forest model demonstrated impressive performance in predicting both stress and non-stress classes, with a maximum accuracy rate of 94.00%. This result highlights the model’s strong predictive ability, ensuring reliable classification of stress and non-stress states. As shown in Fig. 6, the model effectively distinguishes between the two classes, providing valuable insights into the factors that influence stress levels.

Optimized Model Accuracy: 94.00%
Optimized Classification Report:

	precision	recall	f1-score	support
0	0.96	0.92	0.94	99
1	0.92	0.96	0.94	101
accuracy			0.94	200
macro avg	0.94	0.94	0.94	200
weighted avg	0.94	0.94	0.94	200

Figure 6. Random forest classification report.

From the classification report, the model showed consistently high precision, recall, and F1-score for both the stress and non-stress classes, further validating its reliability. Specifically, the precision for the "No Stress" class was 0.96, meaning that when the model predicted a "No Stress" state, it was correct 96% of the time. For the "Stress" class, the precision was slightly lower at 0.92, indicating that while the model accurately identifies the presence of stress, there is still a small chance of misclassification.

The recall values were also high for both classes, suggesting that the model is adept at identifying both stress and non-stress states when they occur. The F1-scores, which balance both precision and recall, were also strong across both classes, demonstrating the model’s ability to make balanced predictions without favoring one class over the other.

The results presented in Fig. 6 visually reinforce these metrics, showing how the model classifies stress and non-stress instances with minimal error. This reinforces the model's suitability for real-time stress detection, making it an effective tool in personalized stress management plans, such as those used in the AyurAura application.

By maintaining high performance across both precision and recall, the Random Forest model can be confidently utilized for applications where accurate detection of stress and non-stress states is critical, ensuring that users receive appropriate interventions based on their emotional and behavioral data.

Fig. 7 presents the confusion matrix for the Random Forest model, offering a detailed view of the model's performance in classifying both the "No Stress" and "Stress" categories. The matrix reveals that the majority of the classifications were accurate, reflecting the model's strong ability to distinguish between the two states.

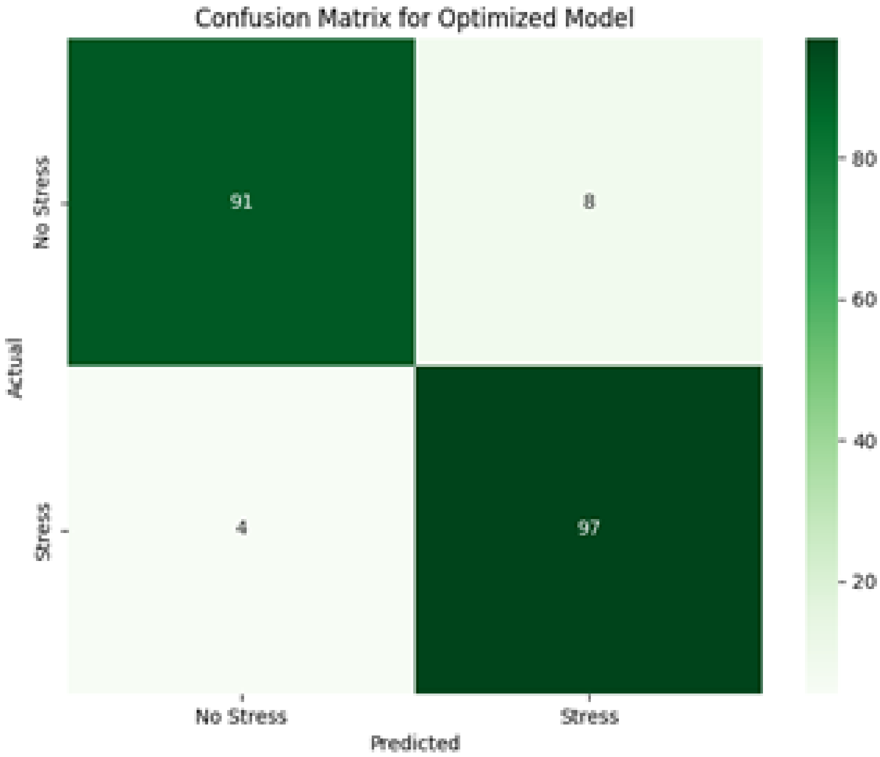

Figure 7. Confusion matrix for random forest

Specifically, there were 91 true positives (correctly predicted "No Stress" instances) and 97 true negatives (correctly predicted "Stress" instances), highlighting the model's overall success in making the right predictions. The high number of true positives indicates that when the model predicted "No Stress," it was correct 91 times, and similarly, the 97 true negatives show the model's effectiveness in correctly identifying stress when it was present.

However, while the model performed well overall, Fig. 7 also reveals some misclassifications, particularly in instances where stress indicators overlapped. These errors are typically due to the complexities in accurately distinguishing between stress and non-stress states, especially when there are subtle variations in the data that lead to ambiguity. For example, certain behaviors or physiological signals might indicate mild stress but not reach the threshold necessary for a strong classification, causing the model to misidentify these cases.

The false positives (where the model incorrectly classified a "Stress" instance as "No Stress") and false negatives (where the model incorrectly classified a "No Stress" instance as "Stress") reflect the challenges faced by the model in dealing with overlapping features. These misclassifications are generally fewer in number compared to the correct predictions but still provide important insights into areas where the model's performance could be further refined.

Understanding these errors is crucial for model improvement. By analyzing the overlap between stress indicators, it may be possible to adjust the model's sensitivity to certain features or incorporate additional data points that could help more accurately differentiate between the two classes. This process of refinement could enhance the model's precision and recall, especially in situations where stress indicators are less clear.

In summary, while the confusion matrix in Fig. 7 shows a strong performance with a high number of correct classifications, it also highlights areas for potential improvement, particularly in dealing with edge cases where stress and non-stress indicators overlap.

The KNN model, although still good, gave a slightly worse accuracy of 92.50%, as clear from Fig. 8. The classification report shows that precision and recall were nicely balanced for both classes, with 0.91 precision for "No Stress" and 0.94 for "Stress", shows that the model was able to classify most cases correctly but sometimes struggled with margin cases.

```
Optimized KNN Model Accuracy: 92.50%
Optimized Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.94      0.93        99
           1       0.94      0.91      0.92       101

    accuracy                           0.93       200
   macro avg       0.93      0.93      0.92       200
weighted avg       0.93      0.93      0.92       200
```

Figure 8.Classification report for KNN model.

Fig. 9. The confusion matrix shows that the model was generally accurate but misclassified some "Stress" cases as "No Stress" and vice versa.

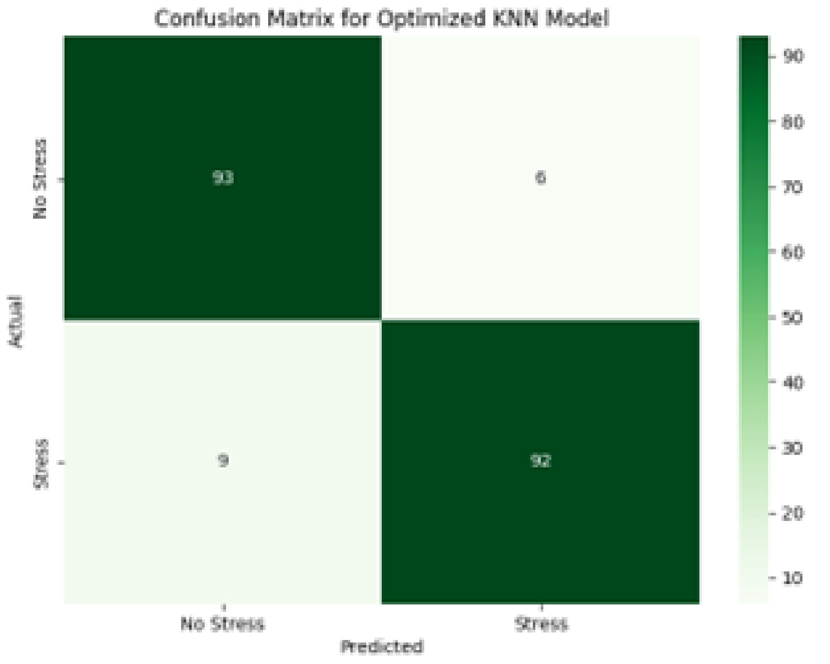

Figure 9. Confusion matrix for KNN model.

The Random Forest model outperformed the KNN model with an accuracy of 94.00% compared to 92.50%. Random Forest performed better in correctly classifying both stress and non-stress cases, whereas KNN performed slightly worse recall for "No Stress" cases, leading to greater misclassifications. The confusion matrices show that Random Forest misclassified fewer cases and is the superior model to utilize when trying to predict stress.

While performing satisfactorily, Random Forest's margin of misclassification indicates that further adjustments (balancing the dataset or fine-tuning of hyperparameters, would enhance its efficiency). Similarly, KNN could be enhanced by more effective feature scaling or tuning the number of neighbors for best classification performance. Ensemble techniques or deep learning approaches may be considered in future enhancements to take the predictive capability of stress assessment models to the next level.

The implementation of the stress prediction and management system was designed to provide users with an interactive and comprehensive solution for managing and mitigating stress through a mobile application. The system was developed with a user-centric approach, integrating predictive analytics and personalized recommendations to assist users in managing their stress effectively.

The front-end of the mobile application was developed using Flutter, a popular open-source framework for building cross-platform mobile applications. Flutter enables a smooth and responsive user experience across both Android and iOS devices, ensuring that users can easily access the features of the application. The intuitive design allows users to navigate through different sections, input behavioral data, and view their stress predictions and recommendations effortlessly.

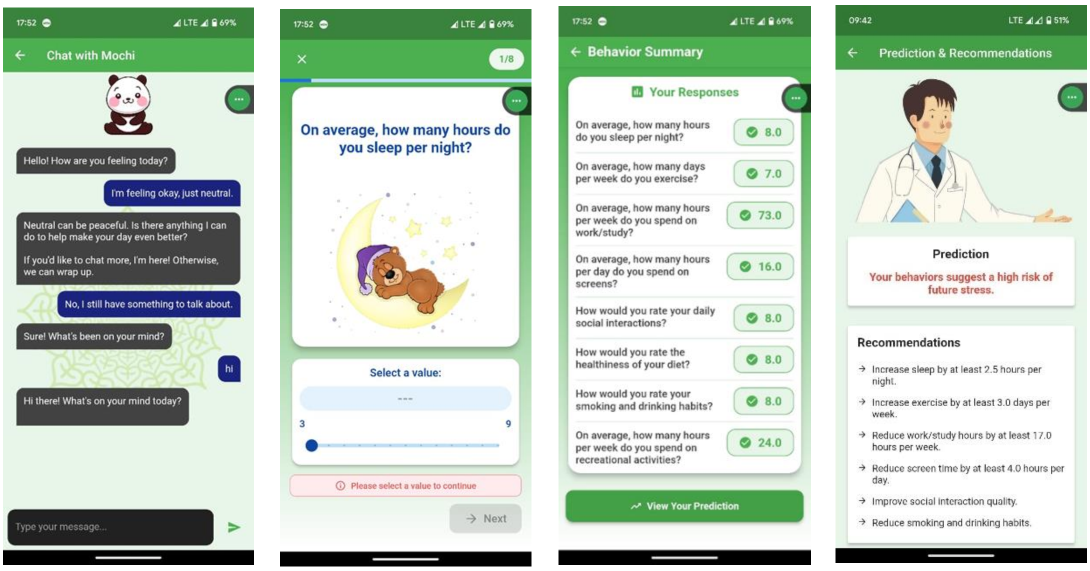

Figure 10 AyurAura application UI

The back-end of the application was powered by Flask, a lightweight web framework for Python. Flask serves as the central hub for managing the app's server-side operations, including handling data processing, user interactions, and the execution of the trained predictive model. The Flask server is responsible for receiving the behavioral data submitted by users, preprocessing it for analysis, and generating predictions regarding future stress likelihood. It then returns personalized advice and recommendations to the app's front-end, where they are displayed to the user.

The core functionality of the app revolves around predicting the likelihood of future stress. Non-stressed users can input their current behaviors, which are analyzed by the app to assess the likelihood of stress occurring in the future. The system uses data from the users' behavioral patterns to predict the likelihood of experiencing stress in the near future. Based on this prediction, the app provides users with customized recommendations on how to maintain their stress-free state. These recommendations might include suggestions for healthier lifestyle habits, activity changes, or ways to better cope with daily challenges.

In addition to the predictive model and behavior change suggestions, the application features an in-built chatbot that offers real-time support during stressful moments. The chatbot serves as an interactive and accessible tool for users who are experiencing high levels of stress. Through the chatbot, users can receive real-time advice, emotional support, and guidance on how to manage their stress in the moment. The conversational nature of the chatbot allows users to feel heard and supported, helping them to regain control over their stress levels.

The Flask-powered back-end contains the trained predictive model, which is at the heart of the application's ability to assess stress and provide recommendations. The back-end processes behavioral data from users, runs it through the model, and returns a prediction of whether the user is likely to experience stress in the near future. Along with the stress prediction, the server also generates personalized recommendations based on the user's behavior and stress level, offering a customized approach to stress management.

For users who provide input data, the app sends this information to the Flask server, where preprocessing is carried out to ensure that the data is in the right format for analysis. After the model predicts the future likelihood of stress, the server sends the results back to the mobile app, which then displays the stress prediction and corresponding advice in an easy-to-understand format for the user.

The integration of predictive analytics, personalized recommendations, and interactive support tools provides users with a holistic approach to stress management. By predicting future stress levels and offering tailored advice, the application enables users to actively work on preventing stress before it escalates.

Ultimately, the mobile application not only helps users in the short term but also supports their long-term well-being by encouraging consistent behavior change and offering ongoing emotional support. By leveraging data-driven insights and interactive tools, the app empowers users to take control of their stress levels, improve their mental health, and achieve a more balanced and fulfilling lifestyle.

4.Summary of Student's contribution

Name	Contribution
Gunasekera H.D.P.M. IT21161674	• Data Collection & Preparation: a) Designed and conducted a large-scale survey with 1,000 participants via Google Forms and in-person surveys to collect behavioral data influencing stress. • Model Development & Implementation: • Evaluation & Optimization: • Frontend Development (Flutter) - Interactive User Experience a) Designed and developed an engaging and user-friendly interface using Flutter, ensuring smooth navigation and real-time updates. b) Implemented a dynamic questionnaire and behavior input system, allowing users to log behaviors for future stress prediction. c) Created a personalized recommendation dashboard, where users receive customized suggestions to change behaviors to stay stress free. d) Development of a motivational chatbot to offer real-time guidance and emotional support to users experiencing stress. • Backend Development (Flask) - Stress Prediction a) Developed and integrated a Flask-based backend, handling data processing, model execution, and user request management. b) Connected the mobile application to a machine learning predictive model, allowing users to assess their likelihood of future stress. c) Implemented a real-time API that takes behavioral inputs, processes them, and returns stress likelihood scores with personalized behavior change suggestions. • Stress Management & Real-Time Assistance a) Integrated an in-app chatbot, offering real-time emotional support and stress management guidance. • Predictive Analytics for Future Stress Prevention a) Developed customized guidance features, ensuring that users receive personalized and actionable insights to maintain a stress-free state. • Scalable, Secure & Efficient System Architecture a) Ensured secure communication between the mobile frontend and backend using efficient API handling. b) Optimized Flask server performance to minimize response times for real-time predictions. c) Designed a scalable architecture, making it future-proof for additional features and user expansion.

5.Conclusion

In conclusion, the integration of predictive analytics for future stress likelihood, coupled with a motivational chatbot, offers a transformative and holistic approach to managing stress that can significantly improve individual well-being. The ability to predict the likelihood of future stress is a crucial advancement in stress management, as it shifts the paradigm from reactive responses—where individuals typically address stress after it has already become overwhelming—to a proactive, preventive strategy that encourages early intervention. This proactive model is based on the premise that early identification of stress can help mitigate its impact before it escalates into a more significant problem.

By analyzing data patterns related to daily activities, behaviors, and lifestyle choices—including sleep quality, exercise habits, work-related stressors, and social interactions—machine learning models are able to recognize subtle but significant trends that precede the onset of stress. For example, disruptions in sleep, changes in physical activity levels, increased work pressures, or a decline in social engagement can all serve as indicators that a person might be at risk of heightened stress. Predicting when these stressors are likely to reach a critical threshold allows individuals to anticipate and prepare for the emotional and physical challenges that may arise, rather than reacting once they are already in full force.

With these predictive insights, individuals can take proactive steps to modify their behavior and reduce the likelihood of stress becoming unmanageable. For instance, they may choose to implement adjustments in their daily routine—such as prioritizing sleep, increasing physical activity, or setting boundaries at work to prevent burnout. Additionally, they can engage in early stress-reduction techniques like mindfulness practices, relaxation exercises, or time-management strategies. The knowledge that stress is likely to occur in the future empowers individuals to make more informed decisions about how they navigate their day-to-day lives, ultimately fostering better mental and physical health outcomes.

Furthermore, the use of predictive analytics in stress management enhances an individual’s sense of control over their own well-being. Rather than feeling helpless in the face of stress, users are equipped with valuable information about their stress triggers and patterns, enabling them to act in advance and take ownership of their mental health. This shift from reactive to proactive behavior helps reduce the severity of stress episodes and ensures that stress management becomes an integral part of one's lifestyle, rather than something that only comes into play during moments of crisis.

In tandem with predictive analytics, the incorporation of a motivational chatbot further enriches this stress management ecosystem. While predicting future stress provides valuable foresight, real-time emotional support is equally critical in helping individuals manage their mental state when they are actively experiencing stress. Many individuals may not have access to immediate human support—whether due to geographical barriers, personal isolation, or hesitation to confide in others—and in such instances, the chatbot offers a crucial, non-judgmental alternative. By providing a safe, anonymous space for individuals to express their feelings and receive guidance, the chatbot bridges the gap between feeling overwhelmed and finding a way to manage stress effectively.

The chatbot's capabilities go beyond simple conversation. It can provide emotional support by acknowledging feelings of stress, offering empathetic responses, and helping individuals feel heard. Over time, as users interact with the chatbot, it learns from those exchanges, enabling it to offer increasingly relevant and tailored suggestions based on individual preferences and past experiences. This adaptability makes the chatbot a valuable tool for personalized, on-demand emotional assistance, especially for those moments when human interaction may not be readily available or desired.

The integration of predictive stress analytics and the chatbot creates a comprehensive and cohesive approach to stress management. Together, they offer individuals both foresight and support, empowering them to take charge of their mental health in a way that is personalized, accessible, and effective. The combination of these technologies ensures that users are not only able to anticipate stress before it peaks but also have immediate support and coping mechanisms available at their fingertips when stress does arise. This dual strategy enhances the individual's ability to manage stress in a holistic and sustainable way, fostering resilience and promoting overall well-being.

Moreover, this approach opens the door for broader societal impact. As more people embrace proactive stress management strategies, there is potential for reducing the widespread effects of chronic stress on public health. Proactive mental health care can help prevent the development of more severe conditions, such as anxiety, depression, and cardiovascular disease, which are often exacerbated by unmanaged stress. By leveraging predictive analytics and chatbot support, we are not only helping individuals cope with stress but also contributing to the reduction of stress-related health issues on a global scale.

Ultimately, the integration of predictive stress analytics and motivational chatbots represents a significant advancement in mental health care. It moves the focus from merely treating stress after it has already taken a toll to preventing it from becoming debilitating in the first place. By giving individuals the tools to identify, anticipate, and manage stress in real-time, we are fostering a more resilient, balanced, and healthy society. This proactive approach offers individuals the knowledge, resources, and support they need to navigate life’s challenges with confidence, leading to improved well-being, better productivity, and a higher quality of life overall.

Together, predictive stress analytics and the motivational chatbot form a holistic system that not only identifies potential stressors but also actively supports individuals in managing them. This approach emphasizes the importance of early intervention and personalized care, ensuring that users receive the right kind of help when they need it most. Furthermore, these technologies can be customized to fit individual lifestyles, making them both accessible and practical for a wide range of users. Whether someone is dealing with work-related pressure, personal challenges, or the demands of daily life, these tools offer tailored solutions that empower individuals to stay ahead of stress and maintain a balanced, healthy life.

Ultimately, this combination of predictive insights and real-time support fosters a more proactive and resilient approach to mental health. By equipping individuals with the tools to recognize stress early and manage it effectively, we contribute not only to their personal well-being but also to broader societal benefits. A healthier, more balanced population is better equipped to thrive in an increasingly demanding world, leading to improved productivity, better interpersonal relationships, and greater overall satisfaction. This proactive approach to stress management represents a crucial step toward fostering a culture of wellness, where individuals have the knowledge, resources, and support to navigate life's challenges with confidence and resilience.

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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,

<u>Confirmation of Dataset Validation and Collection</u>

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.