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Design and Development of mHealth App for Healthcare Professionals' Stress Management in Bangladesh

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Design and Development of mHealth App for Healthcare Professionals' Stress Management in Bangladesh

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Attestation

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Abstract

Healthcare professionals (HCPs) in lower- and middle-income countries (LMICs) like Bangladesh often face high levels of workplace stress, which can negatively impact their mental well-being. However, despite its significant impact, this issue is frequently overlooked, leaving many HCPs vulnerable to burnout and other mental health challenges. Mobile health (mHealth) tools, integrated with wearable devices like smartwatches, have the potential to play a significant role in managing workplace stress among HCPs by leveraging physiological signals. This study explored the design and usability evaluation of a user-centered mHealth tool named '*FreedHCP*,' aimed at managing stress among HCPs in Bangladesh. The research objectives include conducting design requirements and needfinding analysis, developing a high-fidelity prototype, evaluating the usability of *FreedHCP*, and proposing a deep learning (DL) based method for automatic stress detection that could be implemented in future applications. A survey involving 71 HCPs revealed that high workload, patient and family pressure, and staffing shortages were major stressors, while social support, taking short breaks, and time management were effective coping strategies. Participants also indicated a strong preference for app features such as guided meditation sessions, personalized stress management plans, real-time health tracking, and willingness to use a smartwatch-based mHealth app for real-time stress monitoring. Based on these insights, the *FreedHCP* was developed with five core feature categories: 'Assigned Tasks', 'Notification Settings', 'Get Help', 'Wellness Check', and 'Supervisor Dashboard'. The usability evaluation revealed that the 'Smart Monitoring' feature from the 'Wellness Check' category was the most liked, with 29.2% of votes. The app achieved a mean System Usability Scale (SUS) score of 71.77. Moreover, an overwhelming 95.8% of participants expressed willingness to use and recommend *FreedHCP* to colleagues. In parallel, medical students are another vulnerable group significantly affected by mental health challenges such as anxiety, depression, and burnout due to the intense pressures of their academic and clinical environments. These mental health issues, further worsened by a demanding workload and the emotional burden of patient care, can adversely impact both personal wellness and professional development. To address these concerns, a dataset of 886 Swiss medical students was analyzed to automate the screening process for anxiety, depression, and burnout using Machine Learning (ML) and Deep Learning (DL) approaches. The analysis compares the performance of two advanced computational models: an Ensemble classifier, integrating Random Forest (RF), Naive Bayes (NB), and Light Gradient-Boosting Machine (LightGBM), and a Deep Neural Network (DNN). The DNN model emerges as the better performing method by demonstrating accuracy rates of 81.4% for depression, 76.65% for anxiety, and 73.59% for burnout. Comparative analyses further validate the DNN's efficacy against the Ensemble classifier, thereby providing a promising method for automated clinical diagnosis for mental health professionals. This research not only demonstrates the utility of mHealth solutions in stress management but also highlights the promise of Artificial Intelligence (AI) driven models for advancing mental health care in professional healthcare environments.

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1 Introduction

1.1 Background and Motivation

1.1.1 Workplace Stress of Healthcare Professionals

Workplace stress is commonly defined as the harmful physical and emotional responses resulting from a mismatch between job demands and the employee's capabilities, resources, or needs. This stress emerges when work expectations are excessive or resources are insufficient, creating a high-pressure environment where individuals may feel overwhelmed [38]. Healthcare professionals (HCPs), for instance, faces high levels of distress due to both work-related and external stressors, which can heighten anxiety and depressive disorders [87].

High job demands significantly contribute to workplace stress by creating pressures to perform that can lead to feelings of being overwhelmed and a lack of control. Excessive workload, long hours, and pressure from patients and management are cited as key stressors, especially in healthcare settings where heavy demands impact HCPs well-being and patient care [38, 87, 4]. The relentless workload and insufficient breaks exacerbate this stress, reducing employees' ability to cope effectively [4].

Several aspects of the work environment are commonly linked to stress, including high workloads, inadequate resources, and poor management, which contribute to psychological distress [87]. Factors such as role ambiguity, lack of control, negative interactions, and long hours also create a challenging environment for HCPs [38, 37]. The healthcare setting in particular involves managing complex, high-stakes situations with compassion, adding emotional strain [20]. Additionally, issues like inadequate staffing, time pressure, harassment, and lack of positive feedback further exacerbate workplace stress [4].

Workplace stress can lead to a variety of psychological effects, including irritability, anxiety, depression, emotional exhaustion, and burnout, significantly impacting an HCPs mental well-being and job satisfaction [38, 20, 37]. These effects often results in mental and behavioral disorders that diminishes the HCPs ability to perform effectively and empathetically [87, 37]. Workplace stress negatively affects job performance, which in turn compromise quality of care, client treatment, and overall work output [37]. High levels of stress reduce HCPs ability to empathize and meet patient satisfaction, threatening service quality [20, 4].

HCPs use a range of coping mechanisms to manage workplace stress, including problem-centered strategies like identifying problems and planning solutions, as well as avoidance-centered approaches, such as taking breaks or mentally disengaging [38]. Additionally, emotion-centered coping, which includes seeking social support and venting, is prevalent, with HCPs often turning to physical activities to relieve stress [38].

1.1.2 Human-Computer Interaction (HCI)

The primary goals in Human-Computer Interaction (HCI) focus on enhancing user experiences and developing intuitive systems that promote efficiency, usability, and satisfaction [69]. HCI also aims to foster user autonomy and engagement through adaptive design principles, prioritizing user empowerment in goal-driven interfaces [82]. A significant motivation is enabling users to interact seamlessly with technology, encouraging them to achieve their objectives without overwhelming cognitive demands [16].

HCI research is grounded in several core principles, including usability, user-centered design (UCD), feedback, and accessibility. Usability, a foundational concept, ensures that systems are efficient and easy for users, while UCD places the needs and limitations of users at the forefront of development [11]. Additionally, feedback mechanisms are essential in HCI, providing users with real-time responses that guide and reassure them, enhancing their interaction quality [49].

Common research methods in HCI include usability testing, A/B testing, and heuristic evaluations. Usability testing allows for direct observation of user interactions to identify challenges users face. Heuristic evaluation uses predefined principles to evaluate interface design, whereas A/B testing compares versions of an interface to determine effectiveness [86]. These methodologies help in iteratively refining systems to enhance usability and user satisfaction.

HCI systems are typically evaluated through both qualitative and quantitative methods, focusing on metrics such as task success rates, error rates, and time on task. Qualitative feedback from user interviews or surveys complements these metrics, offering insights into user satisfaction and perceived ease of use. The use of metrics for user performance and satisfaction allows for systematic assessment and iterative improvements to meet high usability standards [62].

Recent trends in HCI include the development of multimodal and adaptive interfaces, integration of Artificial Intelligence (AI) driven interactions, and the incorporation of immersive technologies like Augmented Reality (AR) and Virtual Reality (VR). For instance, AI has enabled more intuitive voice-activated and gesture-based interfaces, making interactions more natural and responsive [71]. Such advancements are shaping a future where systems are highly responsive, context-aware, and capable of personalizing user experiences on a large scale [44].

HCI is highly interdisciplinary, integrating fields like psychology, design, and engineering to create effective interaction frameworks. The intersection with AI, for instance, has driven advancements in adaptive interfaces and user modeling, allowing for systems that anticipate and respond to user needs dynamically [62]. Collaboration with fields such as healthcare has also produced HCI systems that improve patient outcomes through efficient data management and accessible design.

1.1.3 User-Centered Design (UCD)

UCD is grounded in principles that ensure the design process revolves around the needs of the users. One key principle is user involvement, where users are included in the design process from start to finish to provide continuous feedback [45]. Another important principle is iteration, which refers to repeated cycles of design, prototyping, and user testing to refine the product [41]. UCD also emphasizes the context of use, meaning that the system should be designed with an understanding of the specific environment in which it will be used [45]. These principles collectively ensure that products are highly usable and tailored to meet user needs.

The UCD process consists of several stages, starting with user research, where designers gather information through interviews, surveys, and observations to understand user needs. This is followed by the design phase, where wireframes and mockups are created to represent potential solutions [17]. In the prototyping stage, designers develop working models of the product, which are tested through usability testing to gather user feedback. Finally, the product undergoes multiple iterations based on test results, ensuring that the final design is optimized for usability [89].

User involvement is central to UCD, with methods such as co-design and participatory design being used to include users in brainstorming and decision-making from the start [31]. In the early stages, users provide insights into their needs and expectations through interviews and surveys, while in the later stages, they are involved in usability testing to validate the product's functionality [42]. Best practices include conducting tests in realistic environments to ensure that feedback reflects actual use cases, and involving users continuously rather than just at the beginning or end of the project [31].

UCD has been successfully applied in industries such as healthcare, software, and automotive design. In healthcare, for example, UCD has been used to design Electronic Health Records (EHRs) that are more intuitive for clinicians, thereby reducing cognitive load and improving efficiency [45]. In the software industry, UCD has been integrated with agile development, allowing for continuous user feedback and rapid iterations to create user-friendly applications [17]. These examples demonstrate UCD's versatility in addressing the unique needs of different sectors.

AI and VR are among the emerging technologies which are shaping the future of UCD by enabling more personalized and adaptive systems. For instance, VR is being used to simulate real-world environments during the testing phase, allowing users to interact with prototypes in a more immersive way, which enhances the feedback process [18]. Additionally, the rise of inclusive design aims to make products accessible to a wider range of users, including those with disabilities, which is becoming a key focus in modern UCD. As remote user research grows in popularity, UCD is also evolving to accommodate global and distributed user groups [34].

1.1.4 Mobile Health (mHealth)

Mobile health (mHealth) apps, which are software programs designed for smartphones and wearable devices, offer a practical alternative for continuous health monitoring [76]. mHealth has evolved from simple Short Message Service (SMS)-based reminders for health appointments to comprehensive apps offering telemedicine, disease tracking, and health monitoring. Its evolution is driven by the widespread adoption of mobile technology, advances in wireless communication, and integration with EHR systems [14].

The primary benefits of mHealth include enhancing healthcare access, particularly in remote or underserved regions, improving patient engagement and self-management, and enabling real-time monitoring of health conditions. These advantages contribute to better health outcomes, reduced healthcare costs, and timely interventions. For example, mHealth interventions have proven effective in managing chronic conditions like hypertension and diabetes, by empowering patients to monitor their health parameters at home [90]. Furthermore, mHealth apps support behavior change by providing tailored feedback and education, which are crucial for patient adherence to health regimens [74].

Key technologies driving mHealth include smartphones, wearable sensors, cloud computing, and mobile apps. These technologies facilitate health data collection and transmission, remote monitoring, and communication between patients and healthcare providers. Wearable devices, such as fitness trackers and smartwatches, collect real-time biometric data like heart rate and activity levels. Cloud platforms store and process this data, enabling seamless integration with healthcare systems. Furthermore, mobile operating systems, particularly iOS and Android, host a wide array of health-related apps that support patient health tracking and telemedicine [36].

mHealth is widely applied in chronic disease management, mental health, telemedicine, fitness tracking, and health education. For example, it plays a significant role in diabetes management by helping patients track their glucose levels and receive tailored advice. Remote monitoring and telemedicine services are also essential, especially in managing conditions such as hypertension and heart disease [79].

Research has shown that these apps can encourage healthy behaviors and facilitate recovery processes through user-friendly and streamlined designs [24]. Through features such as real-time monitoring of vital signs, guided relaxation exercises, and remote consultations, mHealth apps can serve as effective tools for managing stress. Wearable devices complement these apps by passively monitoring user behaviors, allowing for personalized, context-aware, adaptive, and even anticipatory interventions that respond dynamically to the user's needs [24].

In developing countries, mHealth has significantly expanded healthcare access, particularly in rural and underserved regions. Mobile technologies allow healthcare providers to reach patients who otherwise lack access to traditional healthcare services, and also bridges the digital divide by offering cost-effective solutions for public health interventions [9].

1.1.5 Importance of mHealth App in Stress Management

mHealth apps offer a variety of benefits that make stress management accessible, flexible, and affordable. They provide an opportunity for users to access mental health support at any time and place, addressing a significant barrier in traditional mental health support, such as limited access to professionals and services. In particular, they are useful for underserved populations who might face social, geographical, or economic barriers in accessing mental health care [72]. mHealth apps also help reduce stigma associated with seeking mental health support, as users can engage privately without facing judgment or bias [72].

mHealth apps commonly utilize techniques like mindfulness exercises, cognitive-behavioral interventions, breathing exercises, and biofeedback. Mindfulness exercises, in particular, have proven effective for stress reduction by increasing users' awareness and helping them focus on the present moment, which minimizes dwelling on stress-inducing thoughts [57]. Apps incorporating guided meditation or progressive relaxation help users achieve a calm mental state, which is crucial in long-term stress management [32].

Real-time tracking and feedback in mHealth apps empower users to monitor their physiological and emotional states, which aids in better stress management. By integrating continuous data from sensors, such as heart rate and movement tracking, users gain a clearer understanding of their stress triggers, making it easier to implement timely relaxation techniques. Research shows that such data-driven insights encourage users to engage in mindfulness practices when stress indicators arise, significantly enhancing self-regulation and coping skills [75]. Furthermore, feedback on stress reduction practices, such as biofeedback-guided breathing exercises, has been associated with lower perceived stress over time, supporting proactive engagement in stress management [67].

mHealth apps facilitate the integration of stress management practices into users' daily routines through reminders, daily check-ins, and short, accessible interventions [72]. These tools help users develop consistent habits, making stress management a part of everyday life. For example, notifications for quick mindfulness or breathing exercises during high-stress periods reinforce healthy coping mechanisms [72].

1.1.6 Machine Learning (ML) in Stress Management

Machine learning (ML) in healthcare offers critical capabilities for stress management through early diagnosis, continuous monitoring, and personalized intervention. ML algorithms can process large datasets from wearable devices to identify stress patterns and intervene in real-time, providing personalized stress management solutions. By analyzing physiological signals like heart rate and behavioral data from digital platforms, ML enables more nuanced understanding and predictive modeling of stress conditions, which can be life-enhancing for individuals suffering from chronic stress [29].

ML models for stress detection primarily use physiological indicators like heart rate variability (HRV), cortisol levels, and skin conductance, captured via wearable sensors. These indicators are critical in measuring the body's response to stress stimuli. Additionally, psychological indicators such as self-reported mood scores, anxiety levels, and sleep quality are frequently used [88]. These data types combinedly enable the creation of a comprehensive stress profile, which can enhance the accuracy of ML predictions [40].

Data for ML-based stress analysis is often gathered from wearable devices, smartphones, and clinical assessments. This data can include physiological measurements, digital activity logs, and survey responses. Preprocessing steps such as noise filtering, data normalization, and handling missing data are essential due to the variability and sensitivity of physiological signals. One significant challenge lies in ensuring data privacy and maintaining standardized data quality across different devices, as inconsistent data can lead to model inaccuracies [3]. Another obstacle is achieving robustness in ML models, as physiological responses to stress vary widely across individuals [19].

Training ML models in stress management involves using balanced datasets with diverse physiological and psychological signals to avoid overfitting. Evaluation metrics such as accuracy, precision, recall, and F1 score are essential for assessing the effectiveness of these models, particularly in applications where real-time prediction is required. For stress prediction models, metrics like the area under the curve (AUC) are widely regarded as indicative of model reliability, as they assess both sensitivity and specificity [83].

ML models are integrated into real-time applications primarily through wearable technology, which enables continuous monitoring and instant feedback. Devices such as smartwatches can detect physiological changes linked to stress and trigger ML models that classify stress levels in real-time, notifying users when their stress level exceeds a threshold. This setup allows users to receive immediate coping advice or prompts to engage in stress-relieving activities, which improves long-term stress management outcomes [56].

1.2 Problem Statement

HCPs worldwide routinely encounter high-pressure situations and difficult challenges as they perform critical roles in medical care and treatment delivery [24, 30]. The nature of their work demands not only technical expertise but also rapid and often complex decision-making, where each choice can significantly impact patients' lives and overall well-being. Operating in such high-stakes environments places an immense psychological and emotional burden on HCPs, making them particularly susceptible to stress-related conditions, including burnout, depression, and anxiety [24, 22].

When left unaddressed, chronic stress among HCPs not only affects individual well-being but can also endanger patient safety and the quality of healthcare services provided.

Moreover, the stigma surrounding mental health, coupled with time constraints and the misconception that HCPs are inherently resilient, often prevents them from seeking necessary support. As a result, stress and burnout among HCPs frequently go unrecognized and untreated, intensifying the personal and systemic toll of these issues.

In Bangladesh, HCPs face these challenges within a particularly demanding context, worsened by both a high patient-to-HCP ratio and a scarcity of healthcare resources [48]. With over 160 million people and a healthcare infrastructure that remains under-resourced, HCPs are responsible for managing a vast and growing population with limited personnel, facilities, and equipment. Many HCPs work under conditions that can be overwhelming, frequently seeing large numbers of patients in a single day without proper breaks or resources. The burden of these working conditions, combined with expectations to maintain high standards of care, leaves minimal opportunity for HCPs to prioritize their mental health or engage in self-care activities.

Traditional face-to-face counseling and therapeutic interventions offer valuable mental health support but are often inaccessible to HCPs in low-and-middle-income countries (LMICs) like Bangladesh. These interventions require significant time and financial investments, making them less feasible for HCPs who work long hours and may lack sufficient financial resources. Moreover, the shortage of mental health professionals in Bangladesh presents another barrier, as the availability of psychological services remains limited, especially outside urban centers. In addition to logistical constraints, the cultural stigma associated with mental health in Bangladesh often discourages HCPs from openly discussing or seeking help for stress, anxiety, or depression. This stigma not only discourage HCPs from pursuing support but also preserve a workplace culture where mental health is neglected.

In light of these challenges, the demand for scalable, accessible, and cost-effective solutions for managing stress among HCPs is urgent. mHealth technologies present a promising alternative by offering flexible, on-demand mental health support that can be integrated into HCPs' daily routines. These digital solutions can help bridge the mental health support gap by providing accessible tools for self-assessment, stress management, and mental health education. Furthermore, mHealth solutions can be particularly advantageous in resource-limited settings, as they require minimal infrastructure and can be easily scaled to reach a larger population. The ability to personalize these tools to address the unique stressors of HCPs in Bangladesh could greatly enhance their effectiveness, providing targeted support that aligns with the specific needs of the healthcare community.

1.3 Ethical Consideration

The Institutional Review Board (IRB) of our home institution approved the user studies conducted as part of this research (Reference: 2022-SETS-05). All studies were conducted online to ensure convenience for participants. At the start of the surveys, the study's objectives were clearly explained, and participants were required to provide informed consent before proceeding. Consent was obtained by asking participants to write their names and answer "yes" to the first question, indicating their willingness to participate in the study. Only after this step were they granted access to the actual surveys.

1.4 Research Gap

While researchers has explored general stress-management solutions [30], a critical gap remains in identifying the specific workplace stressors that affect HCPs in Bangladesh. Understanding these stressors is essential for developing tailored interventions that address the unique challenges HCPs face in this context. Although studies such as [48] have investigated occupational stress among Bangladeshi nurses, there is still a lack of comprehensive efforts aimed at creating user-centered mHealth solutions that cater to the specific needs of HCPs.

A key element in the development of effective mHealth tools is the involvement of HCPs in the design process. UCD principles emphasize the importance of engaging end-users throughout the development cycle to ensure that the solutions not only meet their needs but are also practical and easy to use in their demanding work environments. For mHealth solutions to be truly effective in managing stress among HCPs in Bangladesh, it is crucial that their feedback and insights are integrated into every phase of the design and development process. This would help in creating tools that are aligned with the specific stressors faced by HCPs in their day-to-day work.

Additionally, the scalability of mHealth solutions makes them particularly suitable for low-resource settings like Bangladesh. With the widespread availability of smartphones and the growing availability of internet services, mHealth interventions can reach a broader audience, providing HCPs with timely support regardless of geographical constraints. This can be especially important in rural areas, where traditional face-to-face interventions may be less accessible. By leveraging mobile and wearable technology, mHealth apps have the potential to offer low-cost, scalable, and sustainable solutions to the pressing issue of workplace stress among Bangladeshi HCPs.

1.5 Research Objectives and Research Questions

1.5.1 Research Objectives

This research aims to develop a user-centric mHealth app, named 'FreedHCP', specifically designed to manage workplace stress among HCPs in Bangladesh. A key feature of the app is its interaction with smartwatches, allowing for continuous, real-time monitoring of stress levels and vital health data.

The key contributions of this work are:

- Identification of workplace stressors and coping strategies among HCPs in Bangladesh.
- Development and usability evaluation of FreedHCP for HCPs in Bangladesh to assist them with real-time workplace stress management.
- Proposing a Deep Learning (DL) based, efficient, and automated stress detection method that could be integrated into the backend of a fully functional stress management app for HCPs in future works.

1.5.2 Research Questions

The study is structured around three central research questions (RQs), outlined below:

1. **RQ1:** What design elements and features should be incorporated into a mHealth app to address the stress management needs of HCPs effectively in Bangladesh?

- **Rationale:** It aims to pinpoint the features and aspects of the app that can effectively cater to the needs of HCPs in managing stress. Important areas to investigate include proven practices (such, as the use of technology, privacy concerns, ease of use, self-tracking features, personalized options, peer assistance, and methods to keep users engaged)

2. **RQ2:** What is the readiness and willingness among Bangladeshi HCPs to adopt a smartwatch-integrated mHealth solution for continuous real-time stress monitoring in their workplace environment?

   - **Rationale:** It is important to gauge their willingness and readiness to devise implementation plans, customize the solution according to their requirements, overcome resource limitations, and encourage acceptance.

3. **RQ3:** How do HCPs in Bangladesh perceive the usability of the proposed mHealth app for workplace stress management?

   - **Rationale:** It is essential to collect their input to guarantee that the app aligns with their requirements, integrates into their routines, and genuinely aids them in dealing with stress. By concentrating on the viewpoints of HCPs in Bangladesh, the app should be customized to suit their circumstances, enhance involvement and acceptance of the app, and enhance its efficiency in addressing the issue of stress management oh HCPs.

To ensure the app effectively addresses HCPs' stress management needs, RQ1 focuses on identifying the essential functionalities and design elements that should be incorporated into mHealth apps. Given that the success of such an app depends on the willingness of Bangladeshi HCPs to adopt a smartwatch-integrated mHealth solution, RQ2 investigates their acceptance of this approach. Finally, RQ3 seeks feedback on the usability and functionality of the proposed prototype to ensure that it meets HCPs' needs and integrates seamlessly into their daily routines.

1.6 Research Outcome

A comprehensive study was conducted to explore the research questions, starting with a survey aimed at understanding the stressors, coping mechanisms, and features preferred by HCPs. Based on the findings, a high-fidelity mHealth app prototype, FreedHCP, was developed, incorporating the identified requirements. User evaluations were then performed to assess the app's usability, functionality, and perceived effectiveness. While prior research, such as [24, 22, 76, 28], has contributed to the development of mHealth apps, there remains a significant gap in comprehensive solutions that address the unique challenges faced by Bangladeshi HCPs. This study aims to fill that gap by adopting a user-centered design approach, focusing on the specific needs of HCPs to guide both the prototype development and its evaluation.

FreedHCP offers an all-in-one solution by integrating features such as AI-enabled chatbots, customized stress management plans, and supervisor oversight, alongside smartwatch integration. The app was designed with the goal of providing a comprehensive approach to stress management, tailored to the specific needs of HCPs in a resource-limited setting like Bangladesh.

Looking forward, the FreedHCP app will enhance its capabilities by incorporating continuous data synchronization from smartwatches, such as heart rate, oxygen saturation levels, and body temperature. Additionally, ML techniques will be employed to classify HCPs' stress levels more accurately. This integration of wearable technology and advanced data analytics will further improve the app's functionality, making it an even more powerful tool for stress management. By continually refining its features, FreedHCP aims to provide a reliable and adaptive solution for HCPs, empowering them to better manage workplace stress and improve their overall well-being.

1.7 Report Outline

Chapter 1 (Introduction):

This chapter introduces the background and the reasons behind it, highlighting the workplace stress faced by healthcare professionals. It covers essential concepts in HCI, mHealth, UCD, and importance of mHealth im stress management, and scope of ML in stress management. Additionally, the problem statement, ethical considerations, and research gaps are defined, alongside the research objectives and **RQs**.

Chapter 2 (Systematic Literature Review):

In this chapter, a Systematic Literature Review (SLR) is conducted to examine existing research on mHealth apps for stress management among HCPs. It describes the methodology used for the review, including search strategies, inclusion and exclusion criteria, study selection, and data extraction. The chapter analyzes the findings of the review, answering **SLR specific RQs (1-6)** about the types of mHealth apps available, their features, psychological interventions, assessment tools, limitations, and security and privacy features.

Chapter 3 (Design Requirements Elicitation and Needfinding Study):

To guide the design of the FreedHCP mHealth app, this chapter details the needfinding study conducted. It outlines the study design, participant demographics, measures used for data analysis, and key findings from the needfinding study. This chapter addresses **RQ1** which is related to the essential design elements and features of the app. It additionally answers **RQ2** about the readiness and willingness of HCPs to adopt a smartwatch-integrated mHealth solution. This chapter contains content from publication [47] titled, "Design and Evaluation of a Smartwatch-Based Physiological Signal-Driven Workplace Stress Management mHealth Tool for Bangladeshi Healthcare Professionals"

Chapter 4 (FreedHCP Prototype and Its Features):

Describing the design and development of the FreedHCP app prototype, this chapter provides the rationale for specific features and functionalities. Key components are highlighted, such as 'Assigned Tasks', 'Notifications Settings', 'Get Help', 'Wellness Check', and 'Supervisor Dashboard'. This overview aims to demonstrate the app's practical applications for stress management. This chapter contains content from publication [47] titled, "Design and Evaluation of a Smartwatch-Based Physiological Signal-Driven Workplace Stress Management mHealth Tool for Bangladeshi Healthcare Professionals"

Chapter 5 (Usability Evaluation):

This chapter presents a usability evaluation of the FreedHCP prototype. It outlines the study design, participant characteristics, and measures used for analysis, particularly focusing on the System Usability Scale (SUS) score. It discusses the findings, and addresses the **RQ3** about user perceptions of usability of the proposed mHealth app. This chapter contains content from publication. This chapter contains content from publication [47] titled, "Design and Evaluation of a Smartwatch-Based Physiological Signal-Driven Workplace Stress Management mHealth Tool for Bangladeshi Healthcare Professionals"

Chapter 6 (Automated Stress Detection among Medical Students):

This chapter explores ML and DL-based approaches for screening anxiety, depression, and burnout among medical students. It discusses the dataset used, pre-processing steps, data labeling, and the selection and development of classification models, including the Deep Neural Network (DNN) and Ensemble Classifier. The chapter evaluates the performance of these models using metrics like accuracy, precision, recall, Receiver Operating Characteristic Area Under the Curve (ROC-AUC), and Matthews Correlation Coefficient (MCC), analyzing their strengths and limitations. This chapter contains content from publication. This chapter contains content from publication [73] titled, "Ensemble and Deep Learning Approaches for Automated Screening of Anxiety, Depression, and Burnout in Medical Student Populations"

Chapter 7 (Discussion):

The key findings from the study are discussed in this chapter, including insights from the SLR, needfinding study, prototype development, and usability evaluation. It analyzes the implications of the findings and discusses limitations, suggesting potential areas for future research.

Chapter 8 (Conclusion and Future Works):

This chapter summarizes the main findings of the study, emphasizing the significance of the developed FreedHCP app for stress management among HCPs. It outlines future plans for the development and improvement of the app, including the integration of smartwatch functionalities and the incorporation of DL-based stress detection methods.

Appendix

The appendix chapter contains two separate parts:

- **Appendix A**: This section provides a comprehensive list of all abbreviations used throughout the report.
- **Appendix B**: This part contains a list of publications that have resulted from this work.

2 Systematic Literature Review

HCPs, who play a wide range of roles in the healthcare industry, are essential to the operation of contemporary healthcare systems. They include doctors, nurses, allied health workers, and administrators. Because of the demanding nature of their work, which exposes them to high levels of stress and burnout, their unwavering dedication to patient care frequently comes at a significant personal cost. HCPs experience elevated stress levels due to the unique stressors present in healthcare settings, including long work hours, intense patient interactions, making life-and-death decisions, and organizational pressures.

Because of the COVID-19 pandemic, mental health issues among HCPs have become more severe, emphasizing the critical need for efficient interventions to help them. Frontline HCPs' mental health has suffered as a result of the pandemic's extraordinary demands, demanding workloads, and mentally taxing circumstances. [33]. By utilizing the widespread use of mobile technology, mHealth interventions have become a viable means of providing individualized and easily accessible mental health support.

Fiol-DeRoque et al. [33] conducted a randomized controlled trial to evaluate the effectiveness of the PsyCovidApp, a mobile phone-based intervention designed to reduce mental health problems among HCPs. Although the intervention significantly improved the lives of HCPs who were already receiving psychotherapy or psychotropic medication, its general efficacy in the general public is still unknown. Golden et al. [39] created and assessed an app for HCPs that builds resilience and uses validated scales to measure mental health parameters. According to their research, a significant percentage of HCPs needed mental health support, which emphasizes the value of focused interventions.

In addition to mHealth interventions, other approaches, such as yoga-based practices, have shown promise in supporting the mental well-being of healthcare providers. Bhardwaj et al. [8] investigated the effects of a 12-week breath and meditation program on burnout and professional quality of life in HCPs with the help of mHealth technology. Their results showed that following the intervention, these outcomes significantly improved.

This SLR aims to promote the mental well-being of HCPs by compiling the most recent data regarding the efficacy of mobile health interventions. This review will focus on answering the RQs set specifically for this review, as mentioned in table 2.1, and will offer insights into the potential of mHealth solutions to address the particular mental health challenges frontline HCPs face by critically analyzing and summarizing the available state-of-the-art research.

2.1 Method

To analyze the research papers on how mHealth apps have been developed or used to monitor the mental health, especially stress, of HCPs, we conducted a systematic review according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Table 2.1: RQs for SLR and their Rationale

ID	RQ	Rationale
RQ1	What types of mHealth apps have been developed and tested to support stress management in HCPs?	Understanding the landscape of existing mHealth apps targeting stress management in HCPs is crucial for identifying gaps and potential areas for improvement in addressing mental well-being in this population.
RQ2	What are the specific features offered by the available mHealth apps that contribute to better stress management outcomes in HCPs?	Analyzing the specific features of mHealth apps helps identify effective strategies for stress management in this population, facilitating the development of more tailored and impactful interventions.
RQ3	How do different psychological interventions, such as cognitive behavioral therapy and mindfulness, incorporated in mHealth apps impact stress management in HCPs?	Understanding the efficacy of various psychological interventions integrated into mHealth apps is essential for determining their effectiveness in reducing stress levels among HCPs.
RQ4	What types of validated assessment tools and questionnaires are integrated into mHealth apps for screening stress and mental health issues in HCPs?	Identifying the types of assessment tools and questionnaires used in mHealth apps helps assess their reliability and validity in screening stress and mental health issues among HCPs, ensuring accurate identification and intervention.
RQ5	What are the current limitations and gaps in the literature regarding mHealth interventions for stress management in HCPs?	Identifying limitations and gaps in the existing literature helps highlight areas for future research and development of mHealth interventions tailored to the unique stressors and needs of HCPs.
RQ6	What security and privacy features are present in mHealth apps that help medical professionals manage stress?	To ensure the privacy of sensitive user data and promote adoption and trust among HCPs, it is imperative to comprehend the level of privacy and security safeguards offered by mHealth apps.

(PRISMA) [1] guidelines as shown in Figure 1. A systematic search was done using Scopus, a large peer-reviewed literature database. The search was limited to studies published in English from 2005 to 2023. It provided papers from multiple authors across various databases that were screened for relevance based on our eligibility criteria.

2.1.1 Search Strategies

At first, we identified keywords that are relevant to our topic. Then we entered the resulting search string, consisting of keyword combinations using the Boolean operators "AND" (must be included) and "OR" (may or may not be included) in Scopus. We restricted our search to the papers' abstracts, titles, and keywords. The initial search

Table 2.2: Lists of Inclusion and Exclusion Criteria

Area Specification	Inclusion Criteria	Exclusion Criteria
Database	**IC1.** ScienceDirect, Springer, IEEE Xplore/Access, PubMed, Frontiers, MDPI, Wiley Online Library, SAGE, World Scientific	**EC1.** Other Journals except for Predatory Journal and journals mentioned ”Inclusion Criteria”
Journal/ Conference Type	**IC2.** Research article	**EC2.** Book Chapter, Reviewed article, etc.
Area of Interest	**IC3.** mHealth Interventions, Stress Management, Healthcare Professional Well-being, Workplace Stress	**EC3.** Areas excluding ”Inclusive Criteria”
Selected Time Period	**IC4.** 2005-2023	**EC4.** Before 2005
App type	**IC5.** Mobile App	**EC5.** Software App

gave us 147 papers. The string used was:

(“stress management” OR “stress reduction” OR “burnout” OR “emotional stress” OR “psychological stress”) AND (“healthcare professional” OR “physician” OR “nurse” OR “medical staff” OR “healthcare worker” OR “doctor” OR “clinician”) AND (“mobile health” OR “mHealth” OR “mobile app” OR “smartphone app”).

2.1.2 Inclusion Criteria

The 147 papers were then assessed against inclusion and exclusion criteria. We got 120 articles after excluding the review paper, short paper, data paper, and abstracts. These articles were screened again manually by reading through the titles and abstracts to assess their relevance to the inclusion criteria which reduced it to 13 papers. Studies were included if they:

- Investigated workplace stress or psychological issues.
- Focused on HCPs.
- Evaluated a mHealth intervention.

2.1.3 Exclusion Criteria

The exclusion criteria that were followed to exclude a study are:

- Book Chapters
- Review Papers
- Papers published before 2005
- Papers that included a Software or Desktop based App as solution

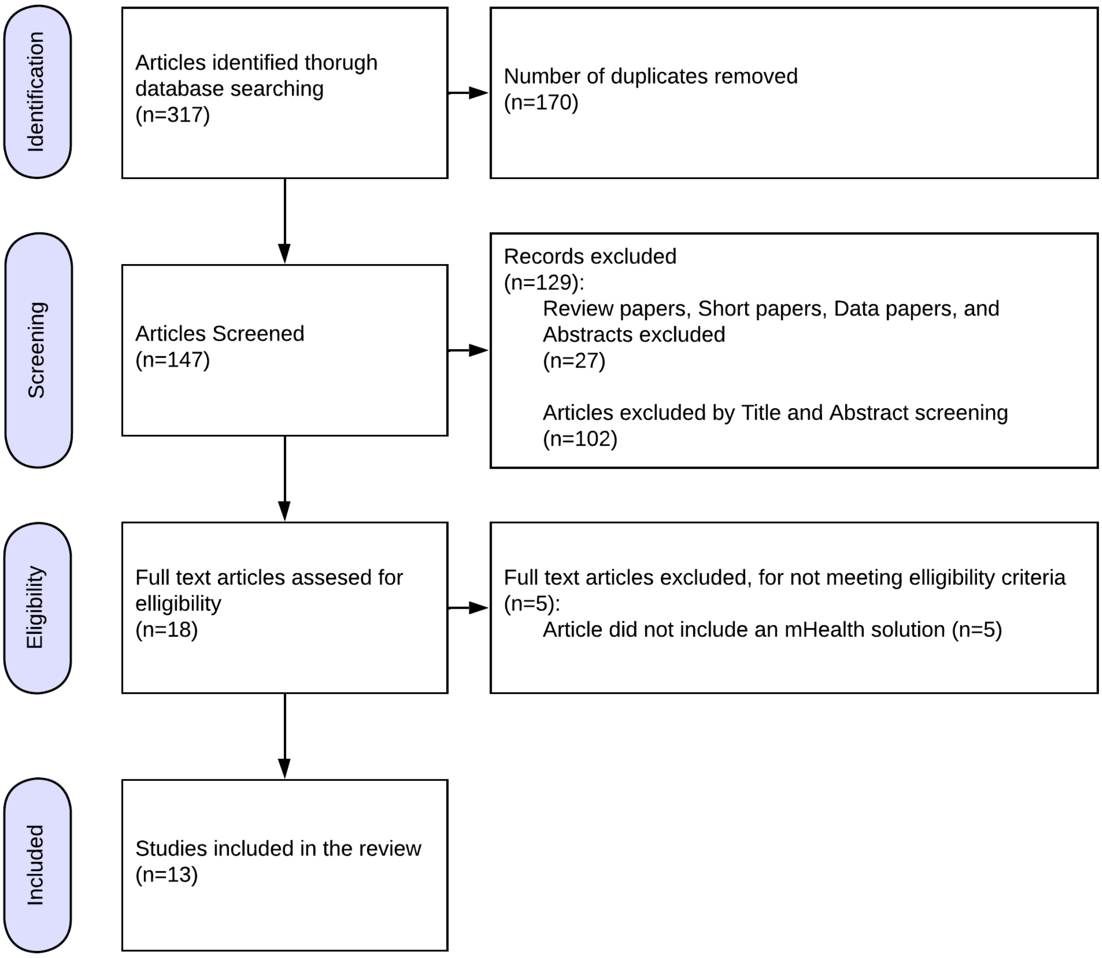

Figure 1: PRISMA flowchart for the literature search process

2.1.4 Study Selection

Initially, 317 articles were found after searching major databases including IEEE Xplore, ACM Digital Library, Springer, Science Direct, Sage, IOP, Willey, Oxford, Taylor and Francis, and Cell. An automation tool called Zotero was used to exclude 170 duplicate articles from the initially acquired papers. Additional 27 short papers, data papers, abstracts, and review papers were excluded since short papers, data papers, and abstracts do not contain detailed information and comprehensive analysis required for this study, and review papers are not applicable for a systematic review. Out of the remaining 120 articles, a majority (n=102) of the articles were excluded after title and abstract-based screening. This indicates that due to common keywords used in the search string, the search result returned a large number of articles that are not relevant to this SLR. Following that, manual full-text screening of the remaining 18 articles was conducted, resulting in the exclusion of 5 articles due to not meeting the inclusion criterion defined in Table 2.2. Finally, 13 articles were selected for conducting this SLR.

2.1.5 Data Extraction

The next phase involved reviewing the full texts of the remaining articles to extract relevant information based on the review topic. As illustrated in Fig. 4., some key categories were predefined to extract the data systematically.

Topical Association

- **Title Based:** Primary screening was conducted based on the title of the articles. Articles were used for this study if the title included workplace stress, healthcare professionals, and mHealth-based mental health management.
- **Keyword Based:** Papers that included keywords “mental health”, “stress”, “mHealth”. “intervention”, “healthcare”, “covid-19”, “doctor”, “app” were used to extract relevant data.

Figure 2: Word cloud based on the keywords

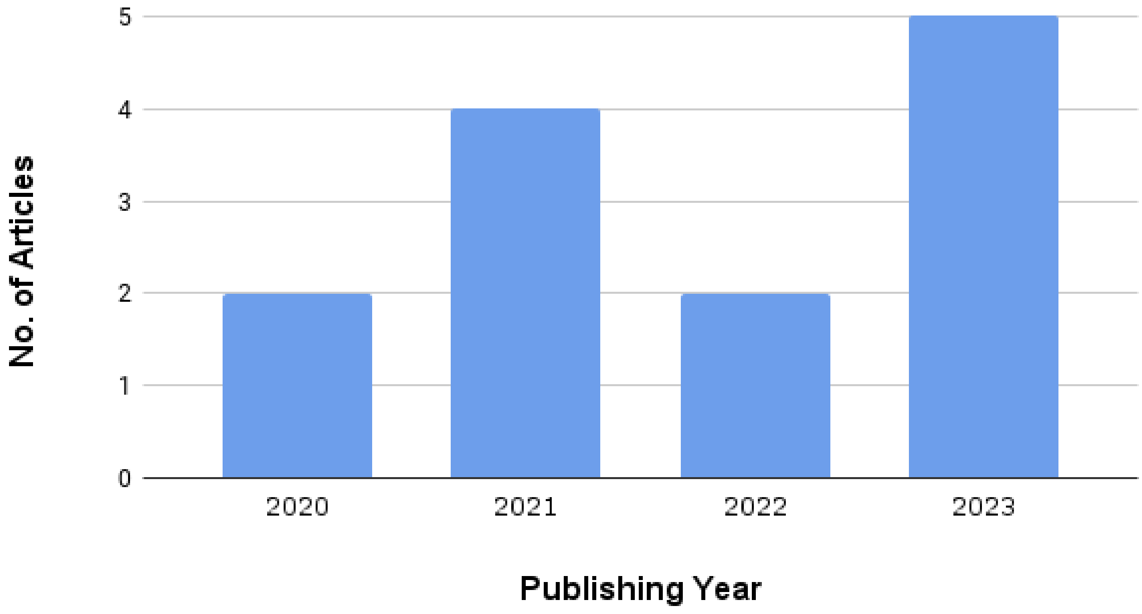

Figure 3: Number of articles published based on year

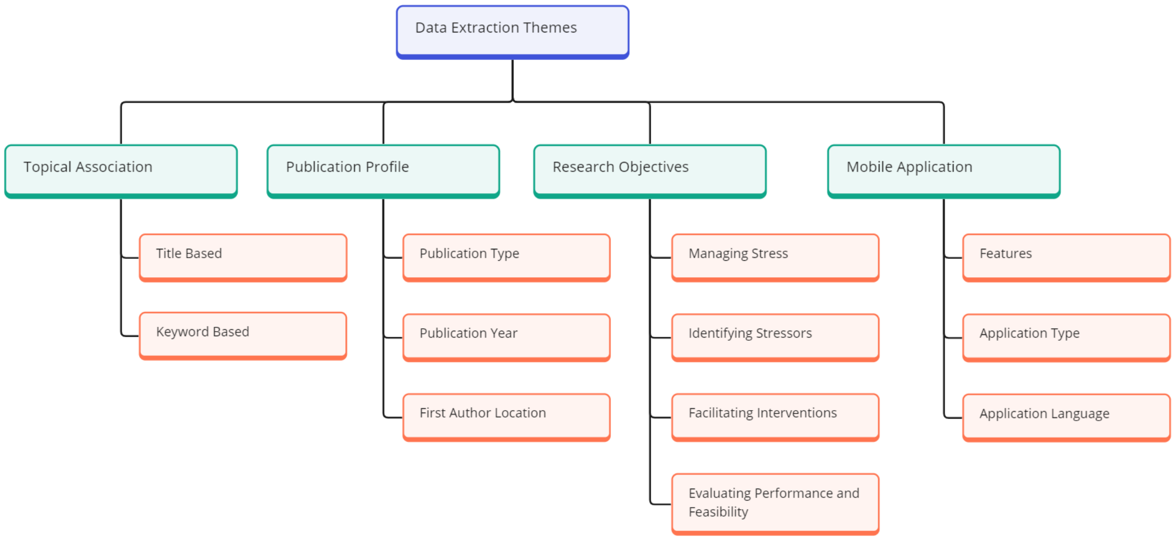

Figure 4: Data Extraction Themes

Publication Profile

- **Publication Type:** The research articles were categorized into conference papers, journal articles, or book chapters based on their publication type.
- **Publication Year:** The publishing year of the selected articles was extracted.
- **First Author Location:** First author locations are extracted to understand which countries are focusing research efforts on stress management of HCPs.

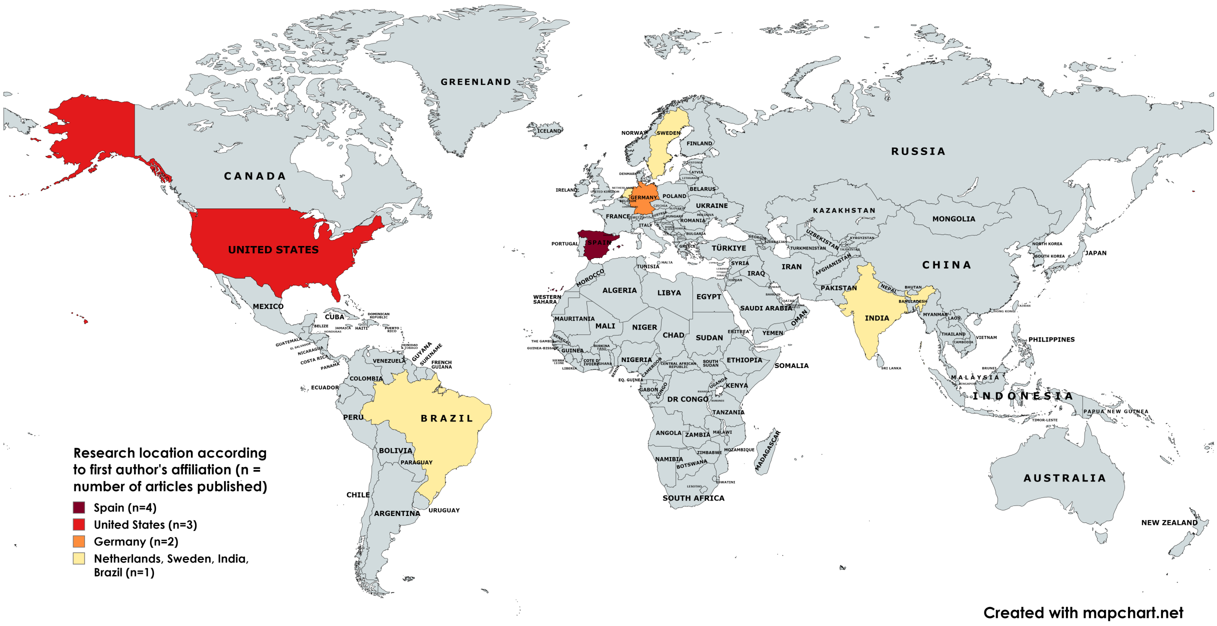

Figure 5: Global distribution of published research papers based on the country affiliation of the first author

Research Objectives

- **Managing Stress:** Relevant data is extracted from the selected articles to understand whether the solution proposed in the article ensures stress management of HCPs.
- **Identifying Stressors:** In this section, the core reasons for HCP stress identified in each article are extracted to realize which tasks or situations act as primary sources of stress among HCPs.
- **Facilitating Interventions:** Interventions that are proposed in articles to manage stress among HCPs are listed below. Some common interventions include breathing exercises, meditation, and social support.
- **Evaluating Performance and Feasibility:** Different performance and feasibility assessment scales used in the selected articles are extracted in this section.

Mobile Application

- **Features:** In this section, the various features available in the mobile app solutions proposed by the articles are listed.
- **Application Type:** This part specifies whether the proposed solution of each article is a mobile app or a combination of mobile and website-based apps.
- **Application Language:** The available language options of each proposed solution are listed to understand the solutions' lingual diversity and target demography.

2.2 Literature Search Outcomes

The association between the selected articles is represented in Fig. 2. using a word cloud. A word cloud is a visual representation where the importance of the words used

Table 2.3: Categorization of Limitations According to Research Articles that Self-Reported Limitations

Categories	Limitations	Research Articles
Study Design and Methodology	Lack of blinding of participants and absence of objective outcome measures, Lack of randomization in sample selection, Small sample size, Difficulty in establishing personal contact with participants during the COVID-19 pandemic	[8], [61], [84], [6]
Intervention and App Usage	Inability to monitor the level of app usage during the trial, Significant variability in app usage and the inability to track user experiences relative to demographics, Unknown long-term effects of the app beyond one month, High work demand and lack of time contributing to non-adherence to the intervention	[33], [78], [39], [85], [77]
Outcome Measures and Assessment	Reliance on self-reported measures such as Maslach's burnout inventory (MBI) and the professional quality of life (PQL) scale, which may be subject to bias, Mental health of participants not evaluated through clinical interviews, but rather using instruments indicated for symptomatology assessment, Questionnaires with known issues such as social desirability, tendency to the middle, common method bias, and subjectivity due to self-perception	[8], [78], [33], [7]
Generalizability and External Factors	Responses of HCPs can be different in other countries, Different challenges and strategies might have been overlooked due to the influence of geographic location on stressors, strategies, or user needs amid the pandemic, Predominantly female participants in the digital health intervention	[64], [61], [77]
Organizational and Professional Perspectives	Lack of consideration for organizational perspectives and challenges in implementing effective stress management strategies for workers during the pandemic, Possibility of biases in article content selection due to the absence of HCPs among the researchers	[25]
Technical Limitations	Evaluation based on a wireframe prototype system, which does not allow evaluation of the full function, Quantitative analysis only evaluates the proposed system with no comparison to a baseline	[23]
Participant Factors	Low level of digital literacy among nurses, High dropout rates possibly due to difficult data collection conditions	[6]

is shown by their font size, while large fonts are used to represent the most important words. According to the word cloud, the most significant words used as keywords among the selected articles are health, mental, intervention, mhealth, covid, stress, healthcare, and workers. This signifies that the research effort in selected articles is centered around mental well-being, healthcare workers, mental stress, and mhealth interventions. Other notable words such as app, digital, mobile, care, design, and telemedicine indicate that developing mHealth-based digital solutions is a significant area of focus in the reviewed articles.

Fig. 3. illustrates the number of articles published in each year from 2020 to 2023. The overall trend of research articles about stress management of HCPs is seen to be following an increasing trend as the number of articles published kept increasing with the exception of 2022 (n=2). The lowest amount of articles published (n=2) was in 2020 and 2022, while the highest amount of articles published (n=5) was in 2023. A noteworthy fact is that research in this area is very recent since the earliest record found of the published articles was in 2020, indicating that the rise of COVID-19 cases worldwide shed light upon the much-needed focus on the mental well-being of HCPs. It is worth mentioning that few articles were found during initial search period of PRISMA method that dated as far back as 2005, however, those articles have been excluded in screening phase due to not meeting eligibility criteria.

Based on the affiliation of the first authors, a world map has been generated in Fig. 5. According to the map, majority of the research (n=4, 30.77%) has been conducted in Spain while Researchers affiliated in USA conducted the second highest amount of research (n=3, 23.08%). 2 articles are affiliated with Germany (15.38%), while rest of the 4 articles has been conducted in Netherlands, Sweden, India, and Brazil respectively. Continental segmentation of research based on geographic location indicates that research effort in this topic has been the strongest in Europe and North America, while only 1 article is published in both Asia and South America, signifying a lack of attention to mental well-being of HCPs in these regions. This serves as a reminder for concentrated effort at further research to be carried out in this topic, specially in the context of Asia where HCP to population ratio is critically low.

2.3 Findings

RQ1: What types of mHealth apps have been developed and tested to support stress management in HCPs?

A lot of apps have been reviewed which is given in Table 2.4. From there some are given below by categorizing where they are trying to make impacts.

1. **Mindfulness and Meditation Apps:** These apps provide meditation and mindfulness exercises aimed at reducing stress and improving well-being. For example, apps like Headspace offer guided meditation on topics such as stress reduction, calmness, and concentration [30].

2. **Cognitive Behavioral Therapy (CBT) and Psychoeducation Apps:** These apps teach stress management techniques through cognitive restructuring, emotional regulation, and problem-solving. Examples include the GET.ON Stress app offers modules on stress education, time management, and emotional regulation [30].

3. **Breathing and Relaxation Apps:** Some apps focus on teaching breathing techniques for stress reduction. For example, Stress-Free Now and BioBase incorporate

mindfulness-based stress reduction through breathing exercises [30].

4. **Wearable-Integrated Apps:** Certain apps are paired with wearable devices to monitor physiological responses to stress, such as heart rate or respiratory patterns, and offer real-time interventions. Stress-Free Now can be combined with a wearable device to provide notifications when significant changes in breathing patterns occur [30].

RQ2: What are the specific features offered by the available mHealth apps that contribute to better stress management outcomes in healthcare professionals?

From Table 2.5 we can see the purposes of these apps which is explained below in details.

1. **Mindfulness and Meditation Exercises**: Many apps provide structured mindfulness and meditation exercises, which help HCPs reduce stress, improve focus, and enhance emotional well-being. For example, Headspace and other similar apps offer guided meditation sessions [30].

2. **CBT Techniques**: Some apps offer CBT-based modules that guide users through cognitive restructuring, emotion regulation, and problem-solving strategies. These help HCPs manage stress by addressing negative thought patterns and promoting emotional resilience. Apps like GET.ON Stress offer this feature [30].

3. **Breathing Exercises and Relaxation Techniques**: Apps such as BioBase and Stress Free Now focus on breathing exercises to regulate stress responses. These techniques are often used in conjunction with mindfulness-based stress reduction to lower stress levels [30].

4. **Real-Time Stress Monitoring via Wearables**: Some apps integrate with wearable devices, such as smartwatches, to track real-time physiological markers of stress, including heart rate, respiratory patterns, and more. These apps provide instant feedback, helping HCPs manage stress as it occurs. Stress Free Now offers this integration [30].

5. **Psychoeducation Modules**: Many apps incorporate educational content about stress and its effects on health, teaching HCPs about stress management strategies, time management, and emotional regulation. GET.ON Stress is one such app that includes detailed psychoeducation modules [30].

6. **Progress and Stress Tracking Tools**: These tools allow HCPs to monitor their stress levels over time, track their progress, and reflect on the effectiveness of the interventions used. Features like online diaries or stress logs are part of this offering [30].

7. **Compassion-Focused and Social Support Features**: Some apps, like the Mindfulness and Compassion with Self and Others program, include features that promote compassion and self-kindness, reducing the negative impact of stress by fostering a supportive mindset [30].

Regarding app languages, the number of languages used is illustrated in Fig 6. English, Spanish, and German were the most frequently reported options, reflecting the locations where most of the reviewed studies were conducted.

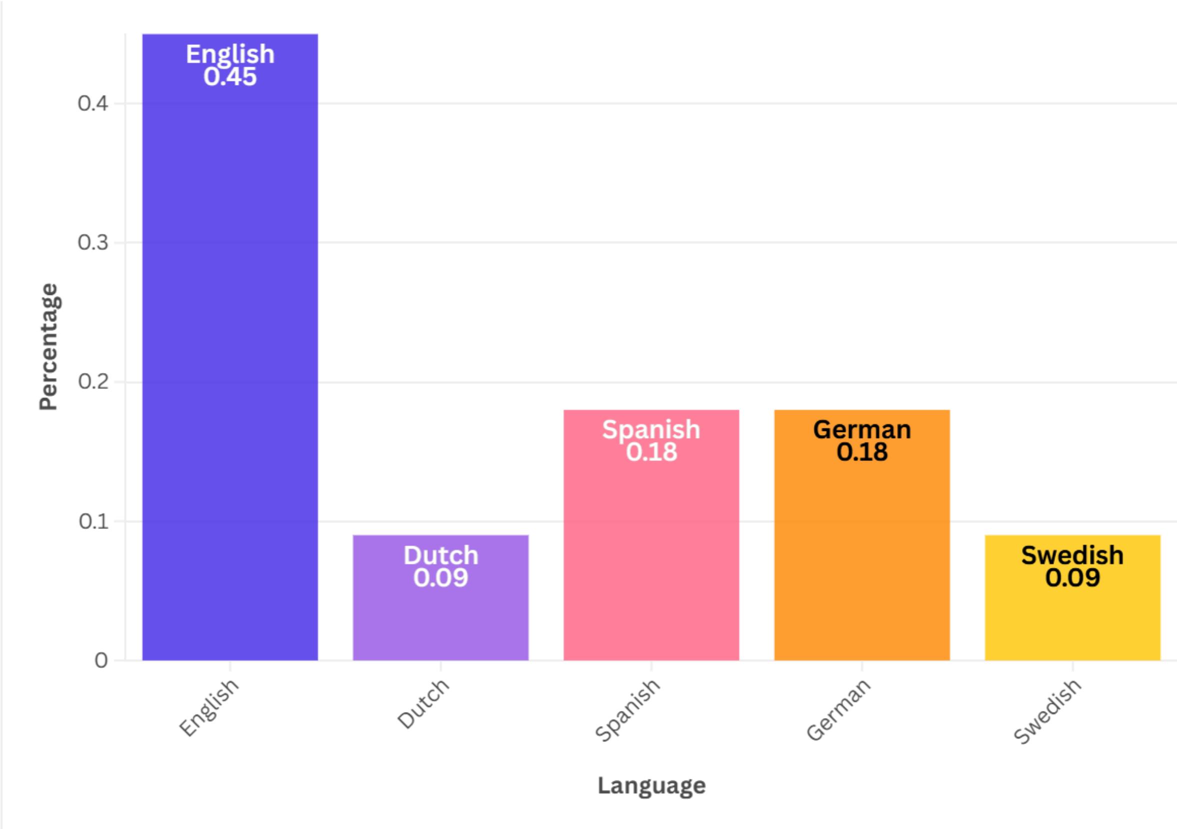

Figure 6: Language Support in mHealth Apps

RQ3: How do different psychological interventions, such as cognitive behavioral therapy and mindfulness, incorporated in mHealth apps impact stress management in HCPs?

Both the psychological interventions like CBT and mindfulness into mHealth apps for HCPs' stress management had contents that was targeting the areas, which are emotional skills, healthy lifestyle behavior, work stress and burnout, and social support [78].

(i) *CBT:*

- Apps with a CBT foundation can give users the means to recognize and confront harmful thought patterns that fuel stress.
- They impart coping skills such as how to decompress, solve problems, and reframe difficult circumstances.
- Apps provide CBT in a self-paced, convenient format that works with the hectic schedules of HCPs.

(ii) *Mindfulness:*

- Apps that promote mindfulness walk users through exercises in present-moment awareness and meditation.
- This can lessen ruminating, improve emotional regulation, and boost resistance to stress at work for HCPs.
- Apps facilitate regular learning and practice of mindfulness techniques.

A lot of apps incorporate several research-proven techniques, such as CBT, and mindfulness. This all-encompassing strategy uses cognitive, emotional, and physiological pathways to target stress. Along with these, the intervention included daily prompts (notifications) that included brief questionnaires to monitor mental health status, followed by short messages offering tailored information and resources based on the participants´ responses [33].

RQ4: What types of validated assessment tools and questionnaires are integrated into mHealth apps for screening stress and mental health issues in HCPs?

For the purpose of screening HCPs for stress and mental health issues, mHealth apps incorporate a variety of validated assessment tools and questionnaires. Among the frequently used instruments are:

(i) The 4-item Perceived Stress Scale (PSS-4) for assessing stress perception [7].

(ii) Standardized measures for perceived team conflict and work-related patterns [7].

(iii) Following the Standard Protocol Items: Recommendations for Interventional Trials (SPIRIT) statement as a guideline for intervention protocol [7].

(iv) Demographic questionnaires, General Health Self-Assessment Scale, Psychological Functioning Scale [77].

(v) Registration with entities like the Brazilian Clinical Trials Registry (REBEC) [77].

(vi) Ecological momentary assessments for mood, along with instruments like 8-item Patient Health Questionnaire (PHQ-8), 2-item Generalized Anxiety Disorder Scale (GAD-2), Post-Traumatic Stress Disorder (PTSD) Checklist for Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) (PCL-5), 2-item Connor-Davidson Resilience Scale (CD-RISC2), 5-item World Health Organization Well-Being Index (WHO-5), Alcohol Use Disorders Identification Test-Concise (AUDIT-C) for conditions like depression, anxiety, PTSD, resilience and alcohol use [39].

RQ5: What are the current limitations and gaps in the literature regarding mHealth interventions for stress management in HCPs?

The reviewed research on mHealth apps for stress management among HCPs has found some key limitations and gaps that need to be addressed, which the authors have acknowledged and presented upfront. The study by Bhardwaj et al. [8] relied on self-reported measures which could be biased, and did not include participant blinding or objective physiological/neurological assessments. According to Fiol-DeRoque et al., [33] the study would not be able to track app usage during the trial, and participants' mental health was assessed using symptomatology instruments rather than clinical diagnosis. The article [39] found high variability in app usage and an inability to track user experiences with demographics. There was a lack of evidence on the association between app usage length and outcome measures in [85], and the app's long-term impacts beyond one month were unknown. While Mira et al. [64] was unable to assess the efficacy of the suggested interventions, Delgado et al. [61] study featured a non-randomized sample, and the authors pointed out that the EASE scale results may differ across different countries. The paper [84] highlighted the small sample size for qualitative. Baumann et al. [7] mentioned problems with self-reported questionnaires and the possibility of bias resulting from rushing through answers and skimming questions. The study in [25] ignored potential regional variations in stressors, strategies, and user needs. It didn't take into consideration the organizational challenges in implementing stress management strategies during the pandemic. Furthermore, the authors pointed out that quantitative research may offer more broadly applicable insights. Secchi et al. [77] observed that the high work demands and time constraints may have contributed to non-adherence to the intervention. Based on the paper [23], the quantitative analysis only assessed the proposal, and the evaluation was based on a wireframe prototype system, which precluded the evaluation of full functionality. Baumann et al. [6] noted challenging data collection circumstances, the absence of push notifications in the app, and frequent synchronization issues between the app and sensor. Recognizing these limitations is crucial for interpreting the findings accurately and informing future research directions in this domain. Thus, we have categorized all those limitations in Table 2.3 to help us better understand the main gaps in the existing literature.

RQ6: What security and privacy features are present in mHealth apps that help medical professionals manage stress?

After examining 13 papers, it was found that only 9 of them addressed mHealth apps. Of them, only one app's features are discussed in article [39] which highlights an anonymous back-end server that contributes to the safe storage of daily emotions, mood reactions, and customized resources on the back end, maintaining user privacy. The papers mostly skip over the particular security and privacy features of the apps, so this remains a gap that needs to be addressed to ensure the sensitive data of HCPs is adequately protected.

Table 2.4: A summary of the mobile applications on mental health for different objectives.

Purposes	Application Name	Brief Description	Features	Platform	User	Reference
To monitor and regulate mental health	Fitcor	Digital coaching of individual stress management	**1.** Direct biofeedback, **2.** AVEM patterns, **3.** Telephone coaching, **4.** Need orientation, **5.** Deep breathing, **6.** Goal setting, **7.** Gratitude journal, **8.** Positive psychology, **9.** Autogenic training, **10.** Body perception, **11.** Sleep habits, **12.** Stretching and yoga, **13.** Fascia training, **14.** Behavior changes, **15.** Activity habits, **16.** Endurance training, **17.** Spine-health	Not mentioned	HCPs	[7]
	Wellness Hub	Supports the resilience and mental health of employees through educational offerings, outreach, clinical care	**1.** Anonymous back-end server, **2.** Notification timer, **3.** Favorites, **4.** My Resources, **5.** My Calm, **6.** My Daily Feeling, **7.** My Daily Mood, **8.** My Stress Reactions	iOS and Android	HCPs	[39]
	StressFree	Provide stress management tools	**1.** Assigned Tasks, **2.** My Notifications, **3.** iChatBot, **4.** Peer Chat, **5.** Smart Monitor, **6.** Infection Check	Prototype	HCPs	[23]
	App	Increase kindness and reduce stress through mindfulness training	**1.** Breathing meditation, **2.** Body scanning meditation, **3.** Shared compassion meditation, **4.** Meditation on compassion, **5.** Resting in presence	Not mentioned	Nurses	[84]
	PsyCovidApp	Prevent and reduce common mental health issues in HCP	**1.** Emotional skills, **2.** Lifestyle behavior, **3.** Work stress and burnout, **4.** Social support, **5.** Practical tools	Not mentioned	HCPs	[78]
	SUPPORT Coach	Provide self-help to diminish negative trauma-related cognition, and strengthen resilience	**1.** Find support, **2.** Self-test, **3.** Calendar, **4.** Manage Symptoms	iOS and Android	Nurses, physicians, ambulance drivers	[85]
	Be + Against COVID	Measure and control stress	**1.** Advice and recommendations, **2.** Self-assessment	iOS and Android	HCPs	[64]
Offer mental health support	Coletivos em Saúde Mental	Enhance mental well-being and reduce stress through remote group therapy and emotional support	**1.** Official government websites addresses, **2.** Mental health preservation guidelines, **3.** Mental health booklet, **4.** Platform access guide	Not mentioned	HCPs	[77]

Table 2.5: Key purposes of the reviewed articles.

Purposes	Brief Description	Reference	Frequency
To manage and reduce stress	It highlights the effectiveness of a 12-week yoga-based meditation and breath intervention program through online sessions in lowering burnout	[8]	8
	Examine acute stress levels in four Latin American nations using the approved EASE scale	[61]	
	Discusses the setup of a digital platform to assist in preventing and dealing with acute stress reactions	[64]	
	A qualitative study investigated emergency care nurses' experiences with an intervention designed to increase empathy and reduce stress using workshops and an app	[84]	
	Assess the efficacy of internet and app-based intervention that offers digital coaching on individual stress coping skills	[7]	
	Make proposals for building stress management mobile apps suited for front-line health professionals using a mixed-methods qualitative approach	[25]	
	Outlines the design and development of a user-centric prototype mobile app to provide stress management help	[23]	
	Examined the influence of personalized, sensor-based mHealth interventions concentrating on stress and physical activity on distress coping.	[6]	
To monitor and reduce post-traumatic stress symptoms	Investigate the effectiveness, usability, and user satisfaction with the built mobile app as a self-help tool	[85]	1
To regulate Mental health	Examine the effectiveness of a psychoeducational, mindfulness-based mHealth intervention in reducing mental health concerns	[33]	3
	Describes the creation and implementation of a mobile app meant to enhance mental health and resilience	[39]	
	Assessed the potential effectiveness of using Balint groups supplied through an m-Health device to promote mental health	[77]	

3 Design Requirements Elicitation and Needfinding Study

Figure 7 illustrates the sequential process involved in developing the FreedHCP mHealth app. The process starts with a background study, aimed at gathering foundational knowledge about workplace stress and the needs of HCPs. This is followed by the design of a questionnaire, used to collect user-specific data that informs the app's design and functionality. Based on this data, a prototype app is created. Next, the development moves to the user evaluation phase, where users interact with the app and provide feedback on its usability and overall satisfaction. This feedback is critical for identifying areas of improvement. In the final stage, the app undergoes refinement based on user input, ensuring that the design remains user-centered and effectively addresses the specific needs of Bangladeshi HCPs.

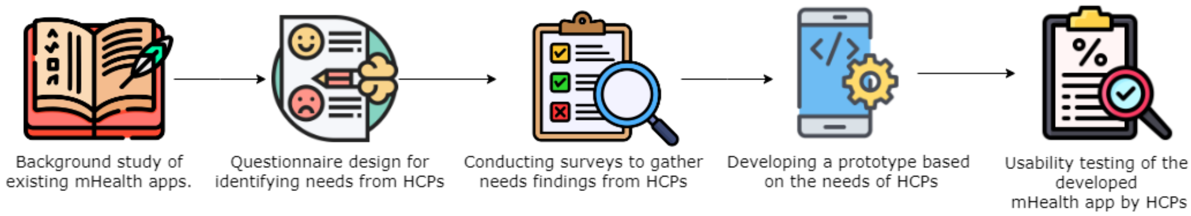

Figure 7: Methodology for FreedHCP stress management mHealth app for Bangladeshi HCPs

3.1 Study Design

We conducted user surveys to determine the needs of HCPs before designing the prototype of the FreedHCP mHealth app. With the assistance of experts, the survey was carefully crafted to collect detailed and relevant data from Bangladeshi HCPs. Participants were informed that the survey would take approximately 20 minutes to complete, and their participation was entirely voluntary and unpaid. HCPs were randomly selected and invited to participate through various mailing lists obtained from local medical universities and hospitals.

Table 3.1: Needfinding Survey Questionnaires

Assessing Stress at Work	
Q1	What factors are responsible for stress in your workplace?
Evaluating Stress Management Practices	
Q2	How do you manage stress at work?
Q3	What kinds of challenges do you face while managing stress at work?
Q4	What resources have you previously used to seek support for managing work-related stress?
Technology and Stress Management	
Q5	Have you ever used any mobile apps for stress management or well-being?
Q6	How important is it for you to have access to real-time stress management tools on a mobile device (e.g., stress tracking, guided relaxation, mindfulness exercises, etc.)?
Q7	What role can technology play in improving stress management for HCPs in Bangladesh?
mHealth App Features and Impact Assessment	
Q8	What features in a stress management app do you believe would be most beneficial to you?
Q9	Would you like to use a smartwatch-based mHealth real-time/continuous workplace stress monitoring, assessment, and management app/tool if available?
Q10	Which physiological factors/signals can be deciding factor(s) for diagnosing stress in human?

Data collection was conducted using a Google Form, which remained open for three weeks, from October 23 to November 12, 2023. Participants could access and complete the survey at their convenience during this period. The survey began with an initial section dedicated to obtaining informed consent and ensuring ethical compliance. This section provided a comprehensive description of the project and its objectives, ensuring participants fully understood the nature of the research. The second section focused on gathering demographic data, such as gender, age, educational background, current employment status, and work location. These questions aimed to capture the diversity of the participants' backgrounds, which is essential for designing a user-centered mHealth app that caters to a broad range of needs.

In the final section, participants were asked about their experiences with workplace stress, current stress management practices, their views on the role of technology in managing stress, and the specific features of mHealth apps that could be impactful. The survey questions were adapted from [24], ensuring a robust framework for needfinding. A selection of some major survey questions from the needfinding study is presented in Table 3.1.

3.2 Participants

3.2.1 Age and Gender Distribution

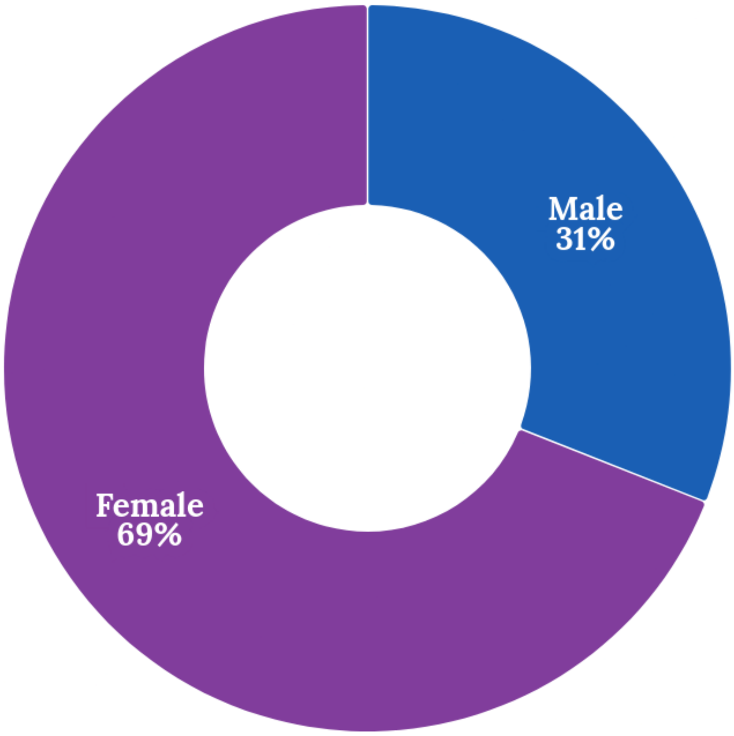

Figure 8: Participants Gender Distribution

Among the 71 survey participants, approximately 69.0% (n=49) identified as female, while the remaining 31.0% (n=22) identified as male, highlighting a well-represented proportion of female HCPs in the sample as shown in figure 8. Figure 9 demonstrates the age distribution of participants, where the majority of participants (62%, n=44) were between the ages of 20 and 30 years. The second-largest group, representing 31% (n=22), fell within the 31 to 40-year age range. A smaller portion of the participants, 4.2% (n=3),

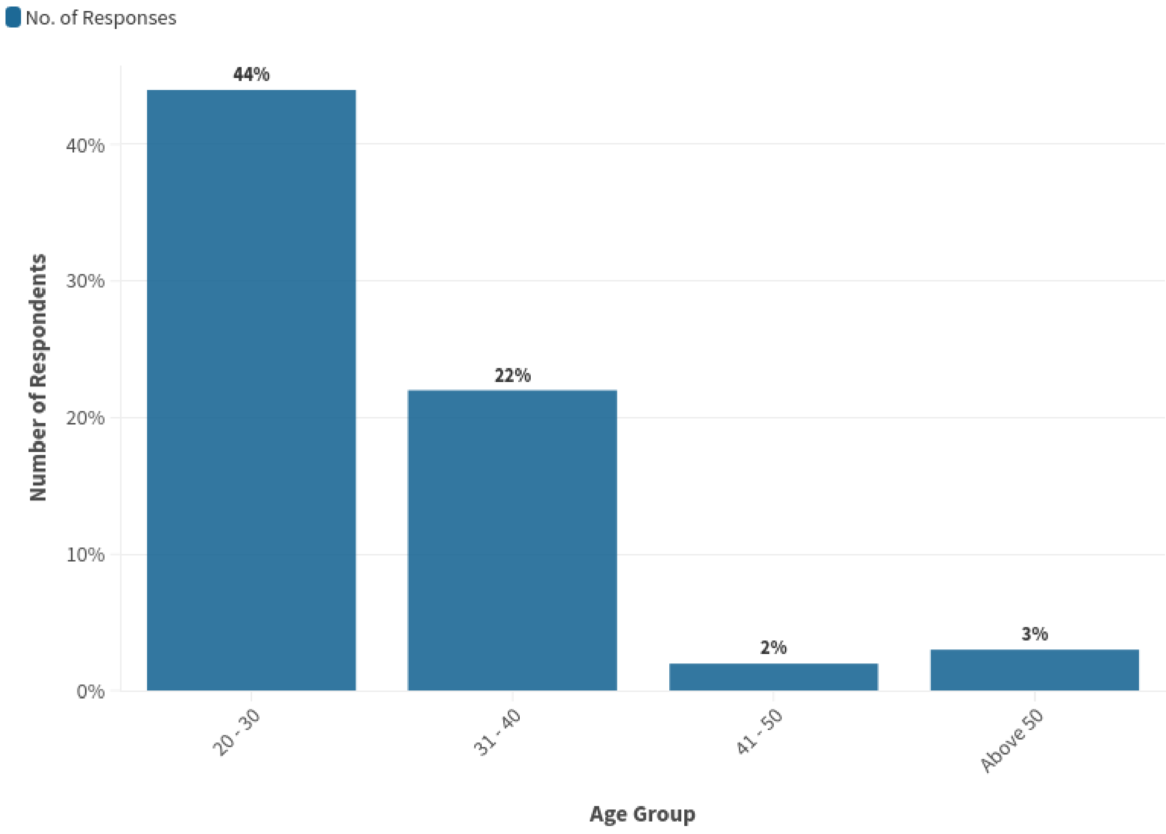

Figure 9: Participants Age Distribution

were aged above 50 years, while the lowest percentage, 2.8% (n=2), belonged to the 41 to 50-year age group.

The overall mean age of participants was 29.93 years, with a standard deviation (SD) of 4.64 years, reflecting a relatively young and homogenous age distribution among the HCPs surveyed.

3.2.2 Employment Status

The employment status of the participants was also assessed, revealing that 73.2% (n=52) are currently employed in various fields, including academia, research, clinical practice, and other related areas. A smaller portion, 7% (n=5), reported being unemployed or actively seeking employment. Students comprised 15.5% (n=11) of the participants, indicating a substantial representation in the survey as shown in figure 10. The remaining 4.2% (n=3) of participants were engaged in specific courses or training programs, further contributing to the diversity of the sample.

3.2.3 Professional Experience

The survey also collected data on the professional experience of the participants. Figure 11 demonstrates that a significant portion, 25 participants (35.21%), reported having 0 to 2 years of experience, indicating that many are early-career professionals. The next category shows a slight decrease, with 22 participants (30.99%) having 3 to 5 years of professional experience. A smaller group, 15 participants (21.13%), reported having 6 to 10 years of experience. There is a further decline, with 6 participants (8.45%) having 11 to 20 years of experience, and only 1 participant (1.41%) reporting over 20 years of professional

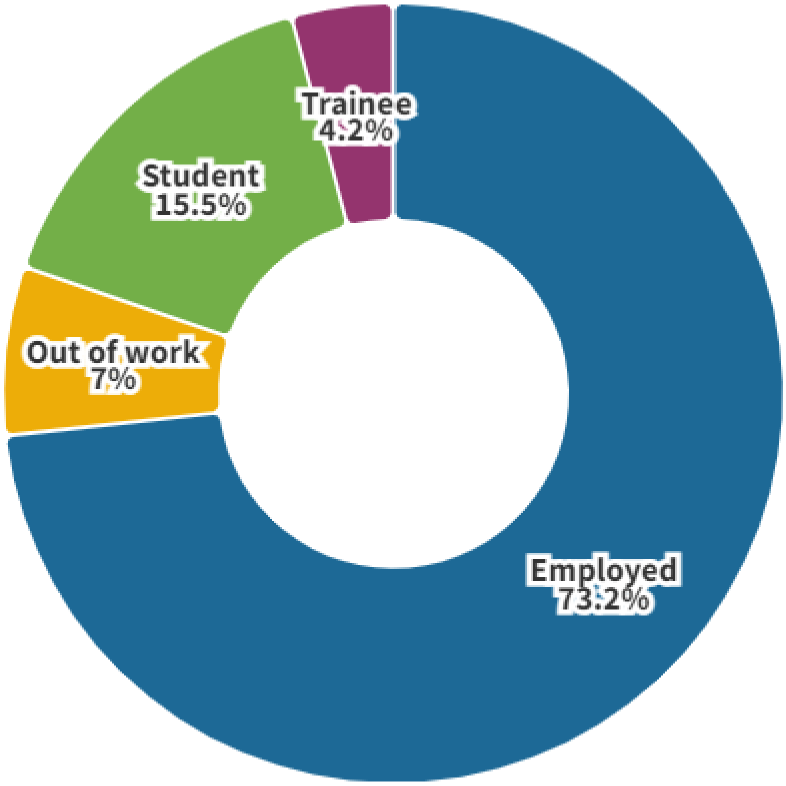

Figure 10: Participants Employment Status

experience. Additionally, 2 participants (2.82%) identified as students who have not yet entered the workforce. This distribution highlights a diverse range of experience levels among the surveyed HCPs.

3.3 Measures and Data Analysis

Participants in the study provided both quantitative and qualitative data as part of a mixed-methods approach. To capture qualitative insights, the survey employed a range of question formats, including multiple-choice, open-ended, yes/no, and 5-point Likert scale questions. Descriptive statistics were applied to analyze the quantitative data obtained from the closed-ended questions, providing a clear overview of participants' responses.

For the qualitative data, thematic analysis was conducted, allowing the identification of key themes and patterns within the open-ended responses. This method enabled a deeper exploration of participants' perspectives, experiences, and needs regarding stress management strategies in their roles as HCPs. Thematic analysis offered valuable insights that enriched the understanding of how HCPs perceive and cope with workplace stress, helping to inform the design and functionality of the FreedHCP mHealth app.

3.4 Findings

3.4.1 Key Stressors

Out of the 71 participants, 52.1% (n=37) reported that a high workload was their primary source of stress. Additionally, 60.6% (n=44) indicated that maintaining a work-life balance was particularly challenging in their roles as HCPs. Other significant stressors

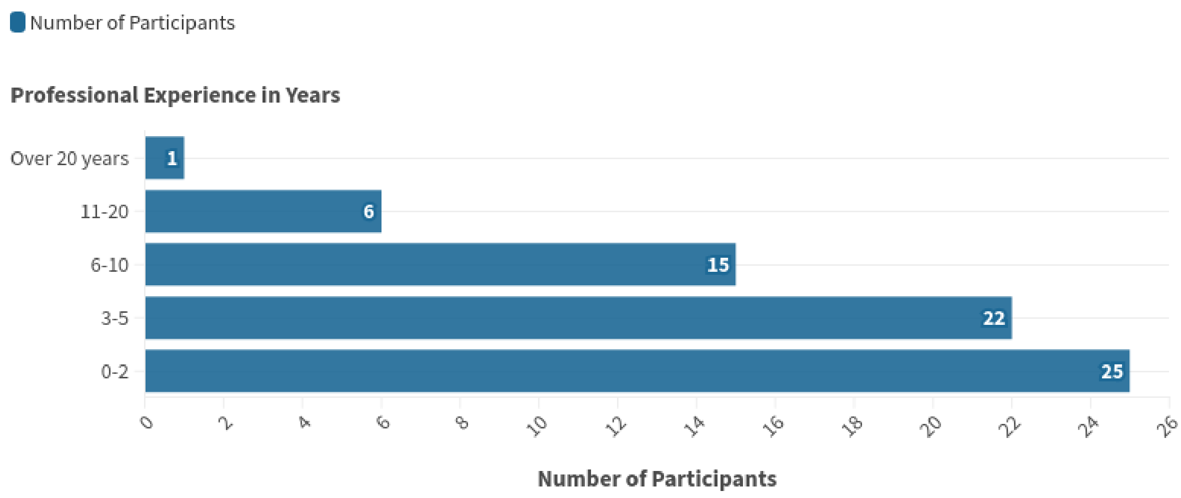

Figure 11: Participants Professional Experience

included staffing shortages, reported by 49.3% (n=35), and administrative burdens, identified by 40.8% (n=29) of participants. Moreover, 50.7% (n=36) highlighted the pressure from patient and family expectations as a major source of stress.

Emotional and psychological stress, time pressure, and the irregularity of shift work affected 36.6% (n=26) of participants. Legal and ethical concerns were another contributing factor for 32.4% (n=23), while 29.6% (n=21) reported stress related to their exposure to infectious diseases. These findings underscore the diverse range of stressors faced by HCPs in their professional environment. Figure 12 visually represents the various stressors identified through the survey responses.

3.4.2 Coping Strategies

All respondents reported using various coping strategies to manage workplace stress. The most widely adopted method was seeking social support from peers and loved ones, as indicated by 50.7% (n=36) of participants. Additionally, 45.1% (n=32) found taking short breaks during the workday to be helpful in reducing stress. Another common strategy, employed by 42.3% (n=30), was the use of effective time management to keep stress under control.

Some participants practiced meditation and mindfulness, with 14.1% (n=10) incorporating these techniques into their routines. Regular exercise was reported as an effective stress-relief strategy by 12.7% (n=9) of participants. However, 15.5% (n=11) acknowledged that they did not have a specific strategy for managing stress, highlighting a potential gap in stress management training within the healthcare sector. Additionally, a few participants (2.8%, n=2) mentioned engaging in unique activities such as travel or hobbies during holidays as part of their stress management approach.

These findings reflect both personal efforts and broader systemic challenges in addressing stress among HCPs. Figure 13 demonstrates the coping strategies identified from the survey.

3.4.3 Challenges in Stress Management

HCPs in Bangladesh face a variety of challenges when it comes to managing stress at work. According to our survey, the most significant challenge is a ‘lack of support’, with 47.9%

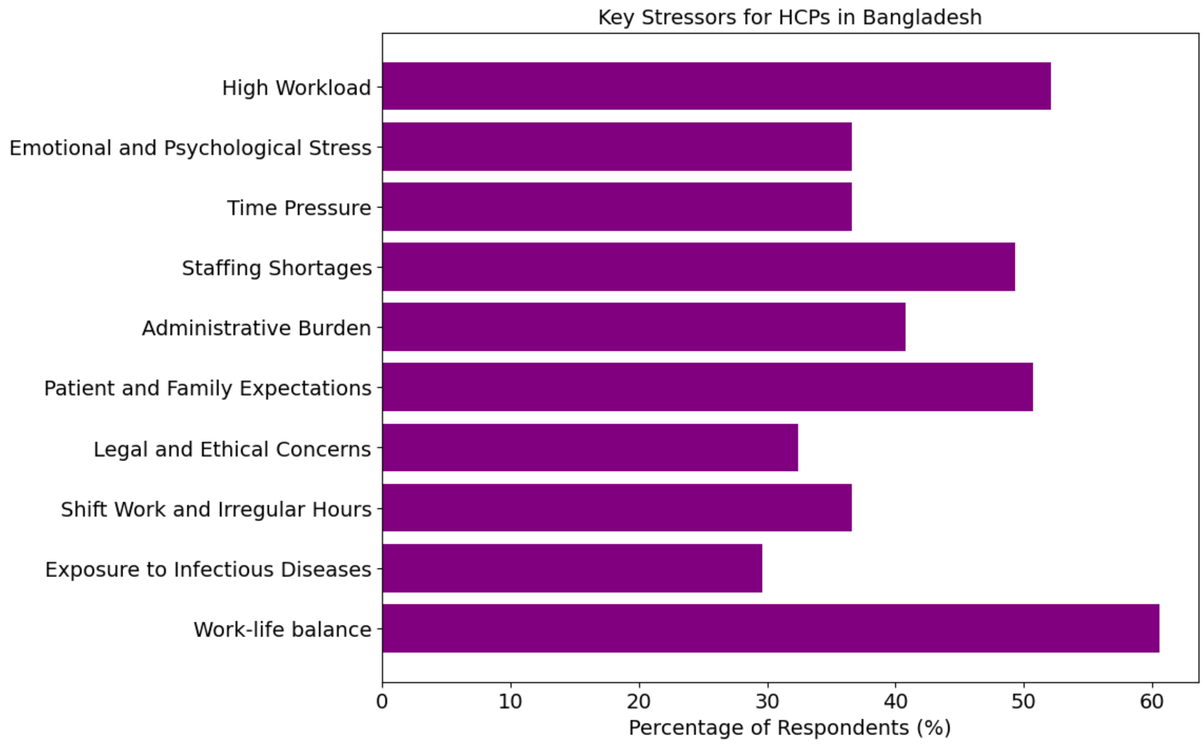

Figure 12: Key stressors identified from survey for HCPs in Bangladesh

(n=34) of participants reporting feeling unsupported by their colleagues, supervisors, or organization. Additionally, 'high workload' was a major concern for 45.1% (n=32) of the respondents.

Another significant issue is 'long working hours', which was reported by 33.8% (n=24) of participants. Similarly, 'patient care pressure' emerged as a key challenge for 38.0% (n=27) of the HCPs. Furthermore, 'administrative burden' was highlighted by 39.4% (n=28), with participants noting that balancing administrative responsibilities alongside patient care is particularly difficult.

These findings emphasize the multifaceted nature of stress management challenges faced by HCPs in Bangladesh. Figure 14 shows the key challenges in managing stress identified through the survey.

3.4.4 RQ1: What design elements and features should be incorporated into a mHealth app to address the stress management needs of HCPs effectively in Bangladesh?

In addressing the stress management needs of HCPs in Bangladesh, technology has the potential to play a crucial role, as indicated by the survey findings. Nearly half of the participants (49.3%, n=35) expressed a desire for 'workplace stress assessment tools' to help monitor and manage stress levels. Additionally, 'telemedicine for mental health' was favored by 42.3% (n=30) of respondents, highlighting the demand for remote mental health support.

'Mobile meditation and mindfulness apps', along with 'real-time stress-tracking' apps, were supported by 36.6% (n=26) of the participants, indicating a strong interest in digital solutions for stress relief. 'Wearable health technology', such as smartwatches that track stress and health metrics, was recognized for its potential by 21.1% (n=15) of the participants.

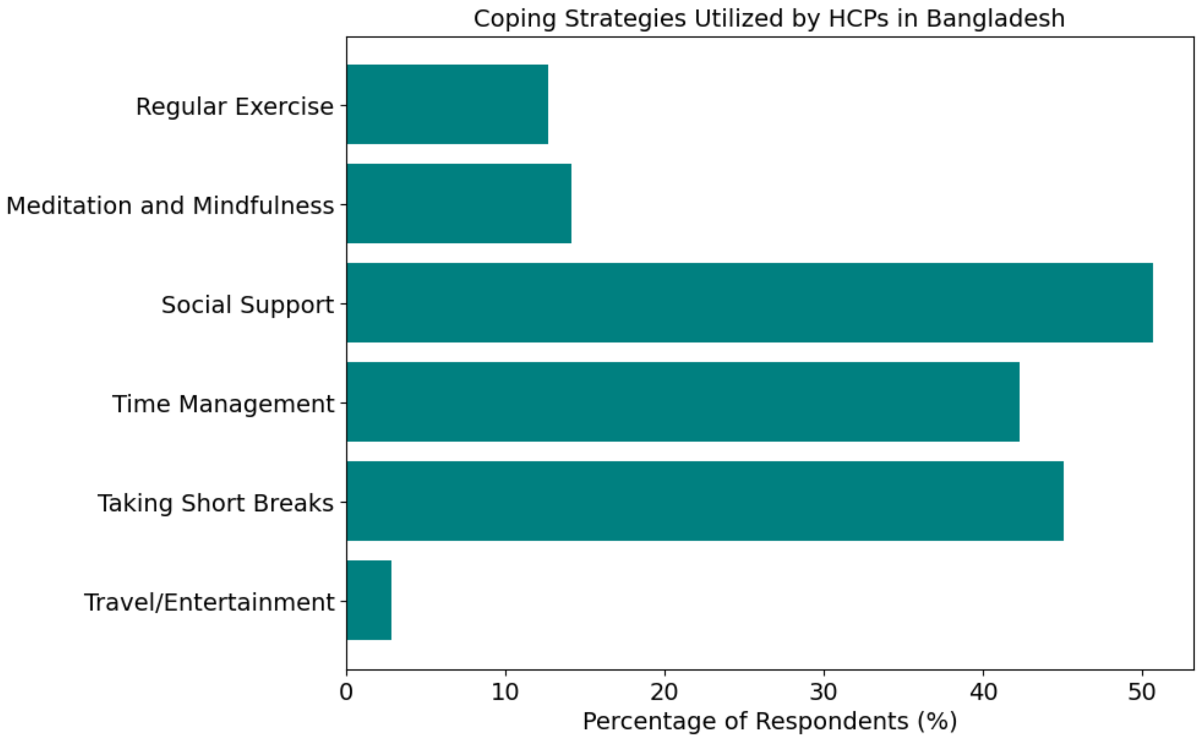

Figure 13: Distribution of coping strategies utilized by HCPs in Bangladesh to manage workplace stress

A small percentage of respondents (1.4%, n=1) were unsure about the role of technology in stress management, possibly reflecting a lack of familiarity with the available technological options. Figure 15 demonstrates the survey findings on how technology can aid in managing workplace stress for HCPs.

The most recommended feature by a majority of participants (56.3%, n=40) was 'Meditation and Relaxation Exercises', highlighting the demand for tools that promote mindfulness and relaxation. Another key feature suggested by 47.9% (n=34) was 'Personalized Stress Management', emphasizing the importance of tailored approaches to stress relief.

'Health Tracking' was favored by 42.3% (n=30), with participants seeking ways to monitor their well-being over time. Additionally, 38% (n=27) of participants recommended a 'Notification about Stress Levels' feature to receive real-time updates and alerts.

The need for immediate support during times of acute stress was reflected in the 36.6% (n=26) who recommended a 'Crisis Helpline' feature. Other suggestions included 'Progress Tracking' (26.8%, n=19) to monitor stress management progress and 'Task Tracking and Manager' (25.4%, n=18) to help manage workload effectively.

These findings reflect the diverse needs and preferences of HCPs for stress management tools. Figure 16 illustrates the recommended features based on the survey responses.

3.4.5 RQ2 (Needfinding Study Phase): What is the readiness and willingness among Bangladeshi HCPs to adopt a smartwatch-integrated mHealth solution for continuous real-time stress monitoring in their workplace environment?

In this survey, we explored the willingness of HCPs in Bangladesh to adopt a smartwatch-based mHealth app for workplace stress management. The results show a strong inclina-

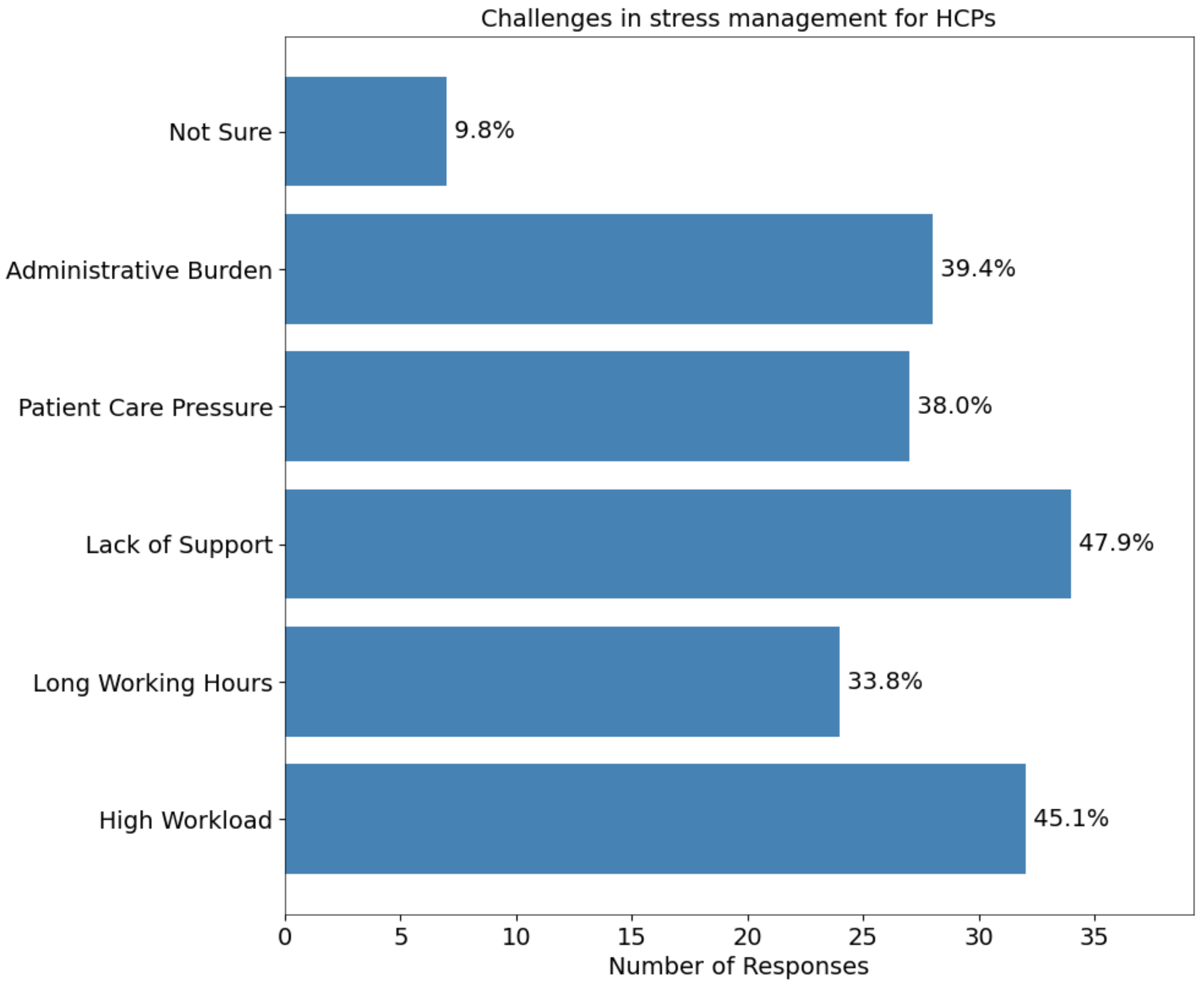

Figure 14: Challenges faced by HCPs in Bangladesh when managing stress at work

tion towards embracing this technology, with 57.7% (n=41) of participants expressing a positive response (yes), indicating a majority readiness to incorporate such a solution into their daily routines.

However, 28.2% (n=20) responded with 'Maybe', suggesting that while they are open to the idea, they may need further information or a demonstration of the app's effectiveness before fully committing. Only a small portion, 14.1% (n=10), answered 'No'. This reluctance could be attributed to concerns such as privacy issues or skepticism regarding the app's efficiency in managing stress.

Given these findings, it is recommended to move forward with the development of a smartwatch-based mHealth app for stress management. Addressing the concerns of the hesitant participants through transparent communication about privacy and the app's efficacy could further increase adoption rates. Figure 17 represents the participants' willingness to use a smartwatch-based mHealth app for workplace stress management during the study.

Figure 15: Role of technology in improving stress management for HCPs in Bangladesh

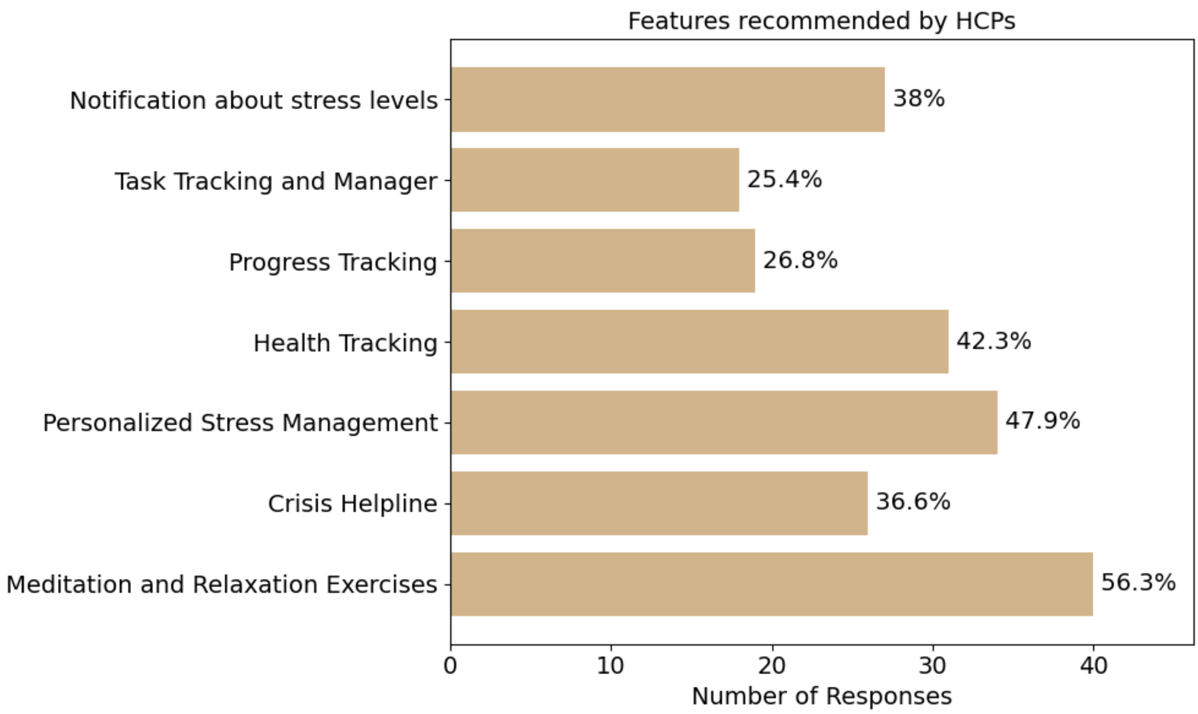

Figure 16: Preferred stress management app functions according to Bangladeshi HCPs

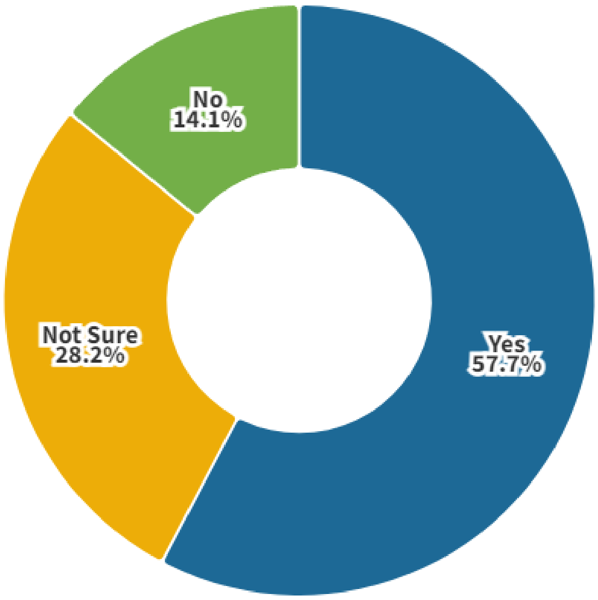

Figure 17: Willingness to use a smartwatch-based mHealth app

4 FreedHCP Prototype and Its Features

4.1 Prototype Design and Development

Before designing the prototype, we identified key features to be integrated into our mobile health app through a thorough analysis of various mental health apps. This analysis was paired with survey data collected from our target user group, which provided invaluable insights into the needs and preferences of potential users. We prioritized ease of use, accessibility, and comprehensive health monitoring as central themes in our development process. After defining these essential features, we moved forward with the conceptualization phase, wherein the app's flow, basic layout, and thematic structure were carefully outlined.

To bring these ideas to life, we utilized FlutterFlow (https://flutterflow.io/), a web-based wireframing tool known for its efficiency in translating concepts into materialistics designs. FlutterFlow allowed us to streamline the design process by simplifying the creation of page layouts and seamless navigation pathways. The result was a high-fidelity prototype that users could interact with to gain a deeper understanding of how the app would function in real-world scenarios. The design focused on an intuitive user experience, where key features would be easily accessible and simple to navigate.

The core concept of the prototype involves synchronizing various health-related data from a user's smartwatch, including placeholders for data such as heart rate, stress levels, and activity monitoring. This information is displayed in real-time and monitored by HCPs, who have administrative access through the app. The supervisor, in this case, creates and manages user accounts for HCPs, allowing them to log in and view relevant health data for their patients. This structure facilitates continuous monitoring and timely interventions when health vitals suggest abnormal levels of stress or physical strain.

The mobile app, named 'FreedHCP', is comprised of several core modules such as Tasks, Wellness Check, Smart Monitoring, Chatbot, and Notifications. Each of these modules is designed to enhance the user's experience and provide critical health insights. Additionally, a Dashboard is provided for the supervisor or HCPs to oversee multiple users' health data in an organized and efficient manner.

FreedHCP also offers general customization options for personnel profiles, such as editing their name, email, profile picture, and viewing recent chats. These customization features, along with the intuitive navigation provided through the home screen and navigation bar, are crucial for ensuring that the app is user-friendly for HCPs and patients alike. As illustrated in Figure 18, the app's home screen provides a clean and organized interface, making navigation straightforward for all users.

4.2 Available Feature Categories

4.2.1 Assigned Tasks

In addition to offering a way to record possible sources of stress, this feature helps users stay focused and organized while managing their work-related tasks. It provides a comprehensive tool for task tracking and stress monitoring, giving users better control over their workload. The Tasks section is divided into two tabs: 'Pending Tasks' and 'Task History'. Figure 19 illustrates how users can view a list of tasks assigned to them by supervisors or self-assigned under the Pending Tasks tab. This feature promotes both accountability and flexibility, allowing users to manage tasks assigned by their supervisors while also adding personal tasks that may contribute to their overall workload.

Users can easily add new tasks through the 'Add Task' option, as shown in Figure 20. By entering task details such as the task name, date, and time, they can independently populate their to-do list, offering a customizable approach to task management. This level of customization is particularly helpful for HCPs who may need to tackle a variety of administrative and patient care responsibilities.

HCPs have the option to mark tasks as completed once finished, and additionally, record their perceived stress level associated with the task at the time of completion, as demonstrated in Figure 21. This self-reporting mechanism is crucial for recognizing how specific tasks or activities impact their mental well-being. Tasks flagged as completed are then stored under the 'Task History' tab, as illustrated in Figure 22, where the user can view detailed information about each completed task, including the task name, completion date and time, and the self-reported stress level.

The data collected in the 'Task History' section allows users to reflect on patterns in their daily work and stress levels. By reviewing this information, users can identify specific activities or times of day that consistently cause increased stress levels. Such insights are valuable for improving time management and workload distribution. Moreover, this feature can help users in developing self-awareness and better understanding their stress triggers, which can ultimately lead to more effective stress management strategies.

4.2.2 Notification Settings

This feature also offers the ability to create personalized alerts for various personal and professional tasks, supporting HCPs in achieving a healthier work-life balance and nurturing positive habits. Reminders can be set for virtually any task or event the user wishes to be notified about, enhancing productivity and well-being. Through an intuitive interface, users can easily manage their notifications, ensuring that no important task or self-care activity is overlooked.

As shown in Figure 23, the interface displays both present and upcoming notifications. These reminders serve a variety of purposes, from prompting users to take short breaks during a busy shift to reminding them to eat at regular intervals to maintain good nutrition. Notifications can also be set for professional tasks, such as meetings, appointments, or the start of a shift, ensuring that users are well-prepared and timely in their responsibilities.

The 'Notification Settings' screen, shown in Figure 24, enables users to fully customize their reminder system. HCPs can add new reminders, specifying the exact time and date for each task or event. Additionally, the settings provide options for users to modify the frequency of reminders or to set notifications a certain number of minutes before the assigned task, allowing for flexibility based on their needs.

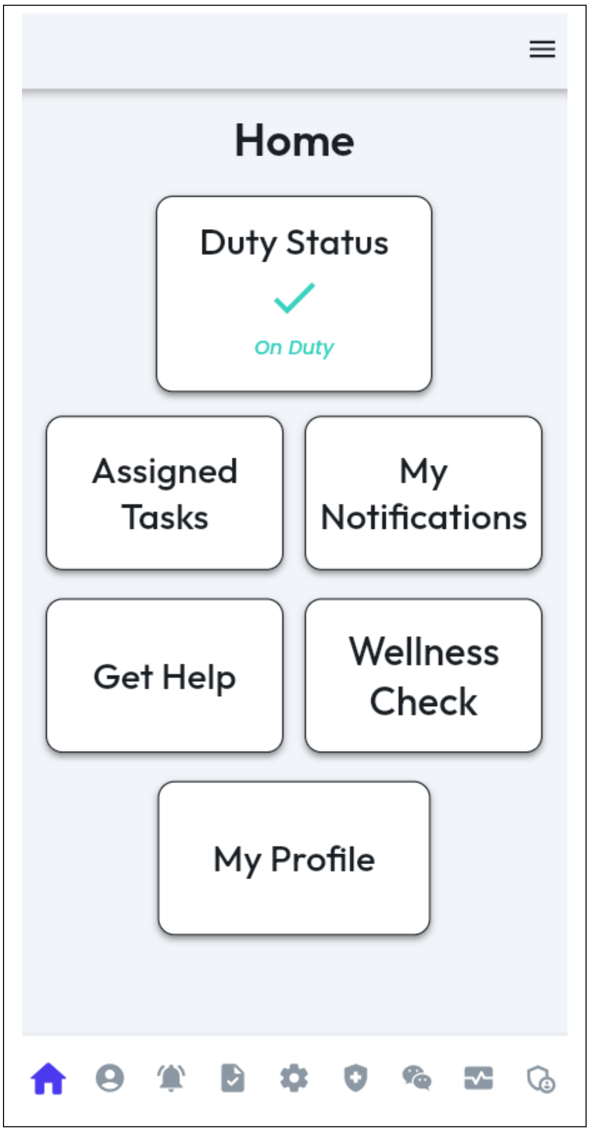

Figure 18: Home Screen

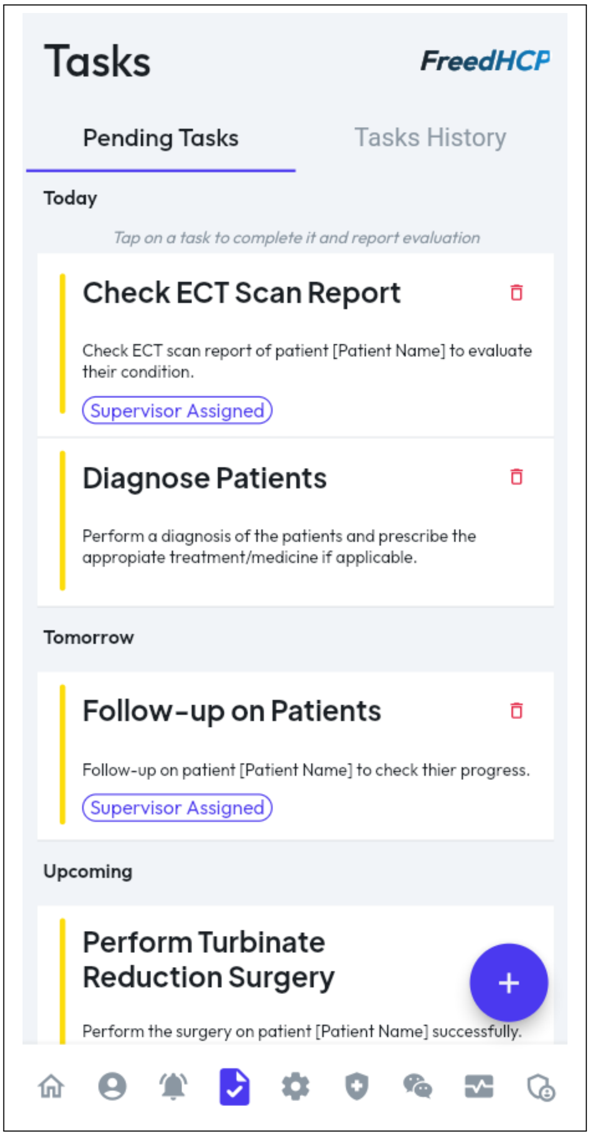

Figure 19: Pending Task

4.2.3 Get Help

The ‘Get Help’ feature stands out as one of the most innovative components of this prototype app, centering around an integrated AI Chatbot designed specifically to support HCPs in managing stress, emotional challenges, and overall well-being. This AI-powered virtual assistant offers continuous support, providing HCPs with a private and safe space to express their concerns, seek guidance, and find relief from the pressures of their demanding profession. The demanding nature of healthcare often leaves little time for HCPs to engage in genuine conversations about their mental health or seek external support. The ‘Get Help’ feature effectively addresses this gap by offering an always-available companion for emotional and mental health assistance.

As demonstrated in Figure 25, based on the issues shared by the HCP, the Chatbot offers evidence-based advice tailored to stress management. This advice may include mindfulness exercises, relaxation techniques, deep breathing exercises, and CBT principles. These suggestions are rooted in scientifically validated methods for managing stress and emotional distress, making the Chatbot a valuable tool for promoting mental health among HCPs who often face high levels of burnout and emotional fatigue.

Moreover, the ‘Get Help’ feature is not limited to stress management alone. As shown

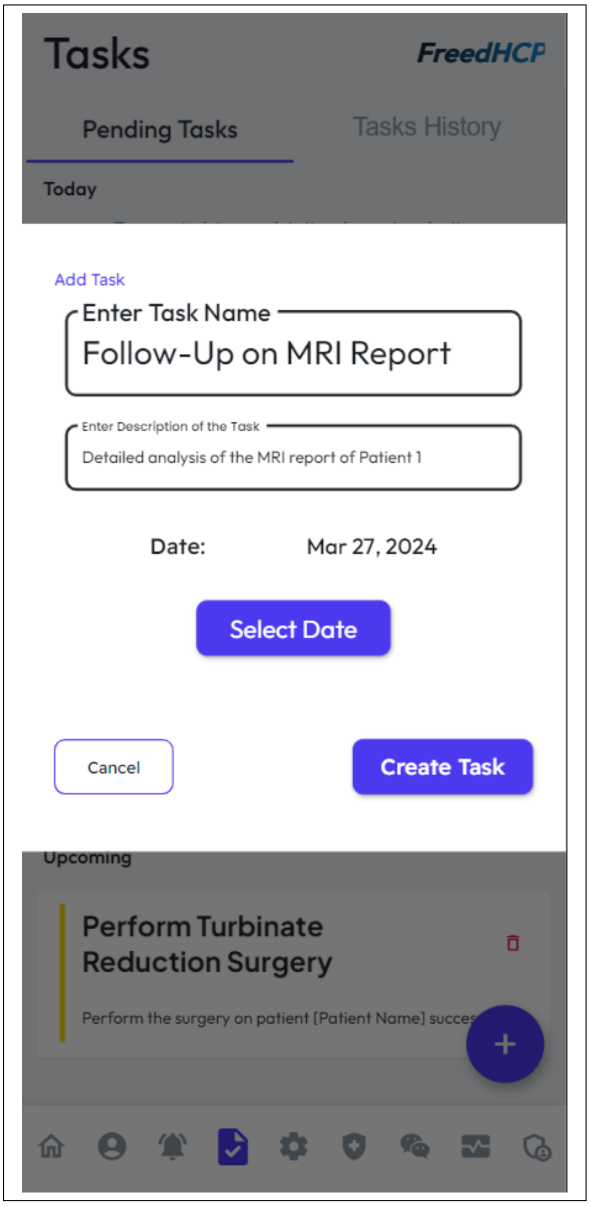

Figure 20: Add Task

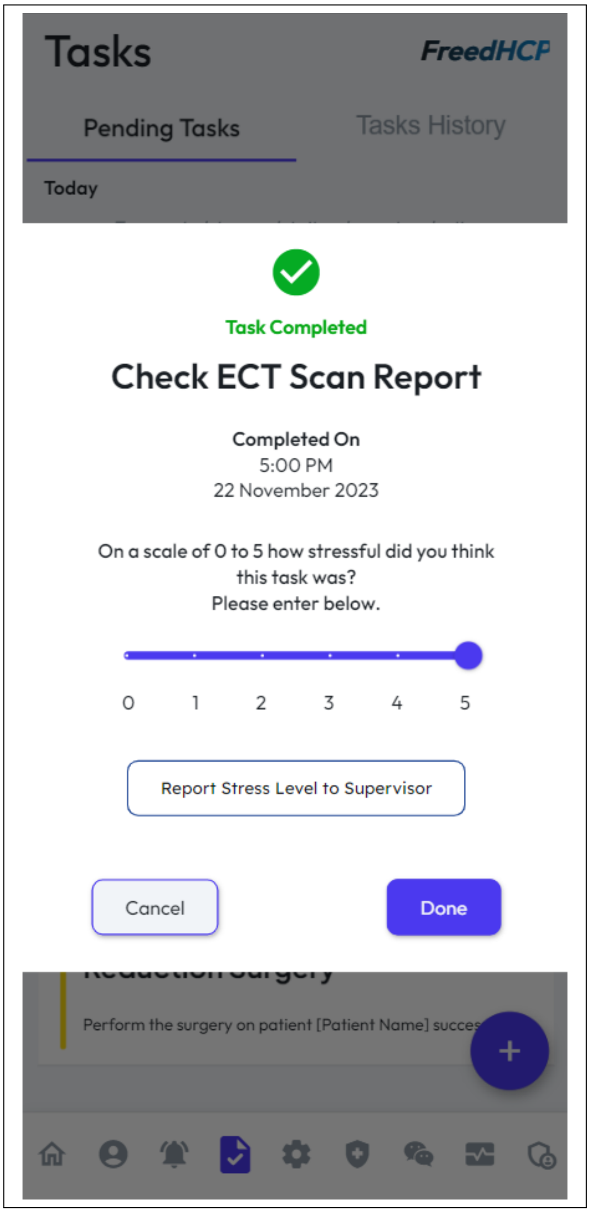

Figure 21: Finish Task

in Figure 26, if the user grants permission, the app stores previous conversations automatically. This functionality allows users to revisit past interactions with the Chatbot, enabling them to reflect on previous challenges and the advice they received. This can be particularly helpful for users who may want to track their emotional progress over time or review stress management strategies that worked in the past. The ability to store and access chat history adds a layer of continuity to the support the Chatbot provides, making it a reliable companion for HCPs as they navigate ongoing personal and professional stressors.

In addition to stress management, the Chatbot offers personalized guidance on self-care practices and work-life balance, two areas that are often neglected in the busy schedules of HCPs. The 'Get Help' feature encourages HCPs to adopt sustainable self-care habits, promoting activities that enhance both mental and physical well-being. Whether it's a suggestion to take a walk, engage in a quick meditation session, or manage their workload more effectively, the Chatbot provides practical tips that users can integrate into their daily lives.

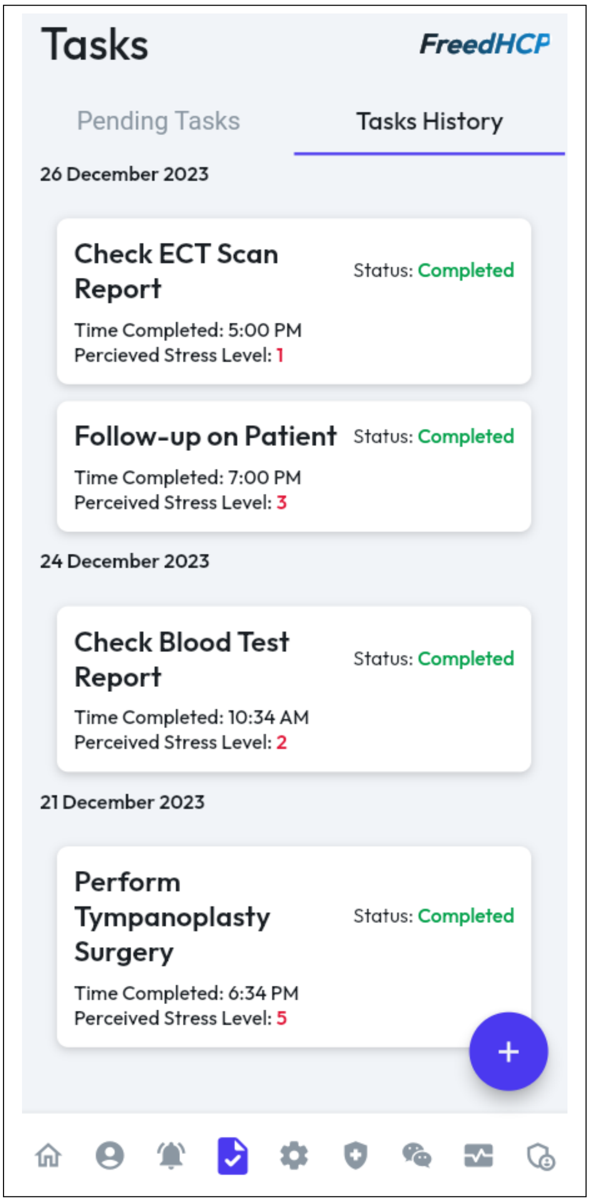

Figure 22: Task History

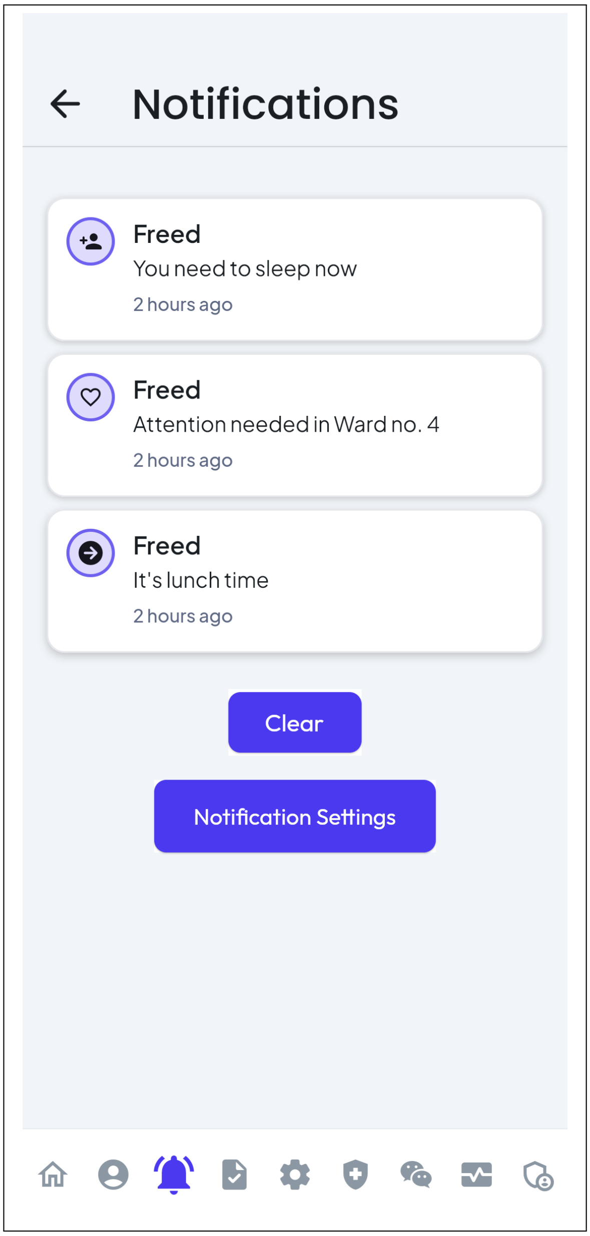

Figure 23: Notifications

4.2.4 Wellness Check

HCPs can utilize this feature to actively monitor their vitals through seamless integration with their smartwatches. The app collects and synchronizes real-time data from the wearable device, allowing HCPs to easily track their physical and mental health. This integration of wearable technology empowers users to take proactive measures in understanding their health status, making it easier to manage their well-being amid the demanding nature of their profession. As shown in Figure 27, the app presents a detailed dashboard with a user-friendly interface that organizes and displays key health information in an easily interpretable manner.

The dashboard showcases recent data collected from the user's smartwatch, including metrics such as heart rate, blood pressure, oxygen level, body temperature, and stress levels. The app continuously updates this data in real time, providing HCPs with a comprehensive overview of their current health status. Stress levels are represented with severity ratings, making it easier for users to quickly gauge how their mental and emotional state has fluctuated. This real-time feedback ensures that HCPs can stay informed about

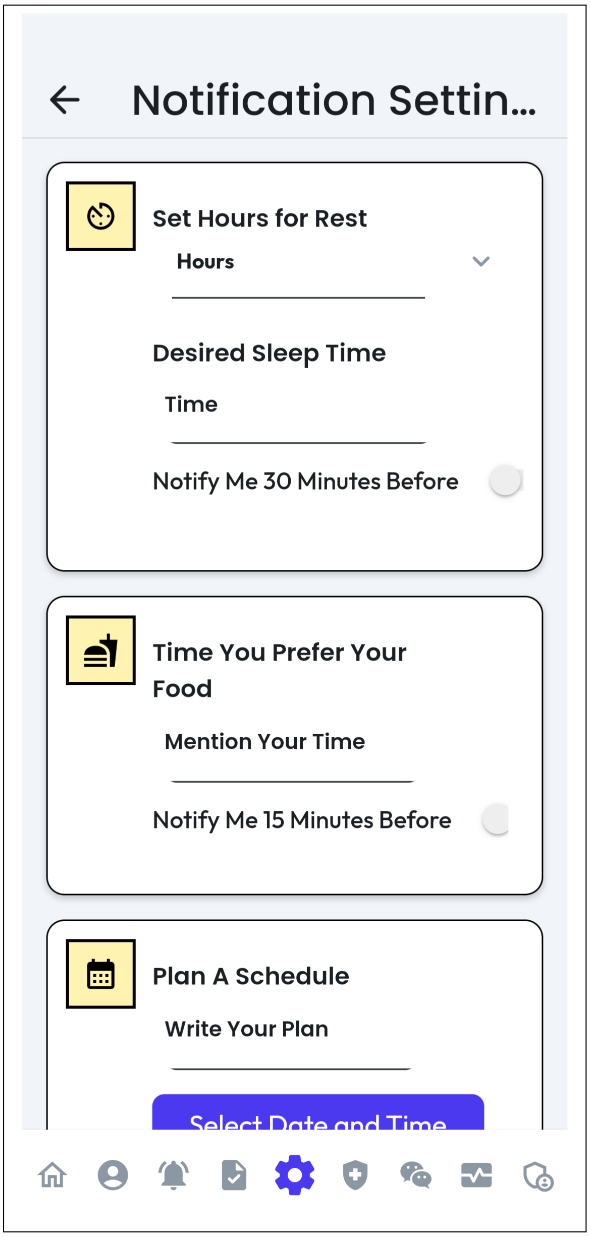

Figure 24: Notification Settings

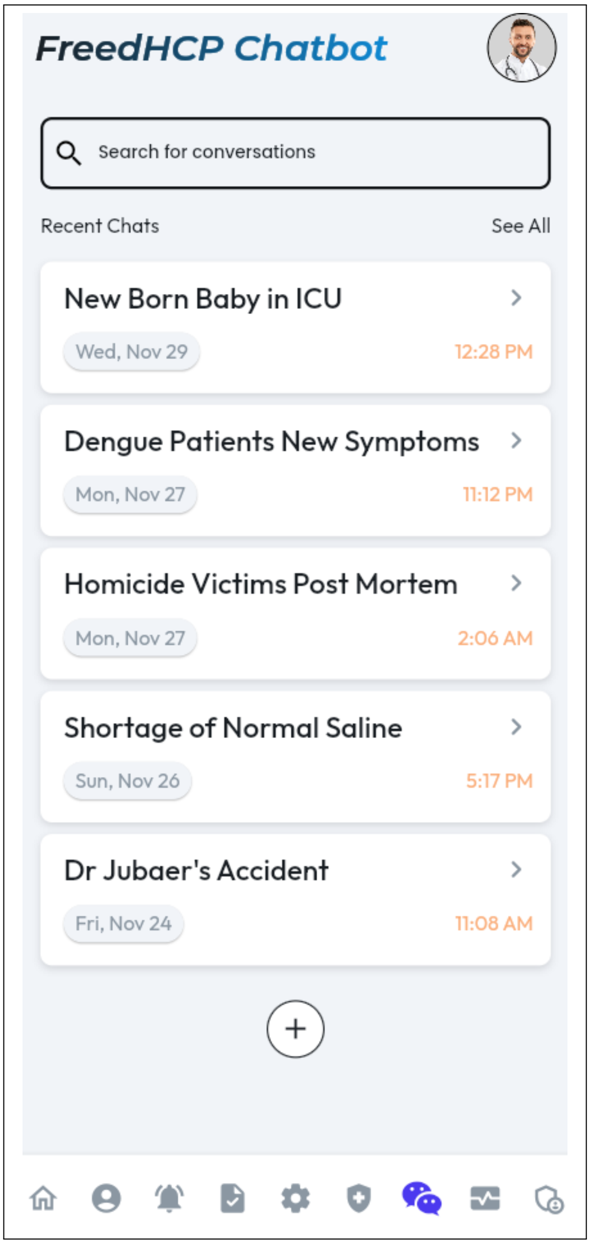

Figure 25: Chatbot Menu

their well-being throughout their workday, enabling them to make informed decisions about self-care or potential interventions.

Additionally, as illustrated in Figure 28, color-coded visual indicators help users easily interpret the data. These color codes highlight the severity of the user's stress levels, making it visually intuitive to identify areas of concern. For example, low-stress levels might be indicated by green, moderate levels by yellow, and high levels by red, prompting immediate attention. This visual approach not only simplifies data interpretation but also enhances the overall user experience, enabling HCPs to quickly assess their health status without needing to manually analyze complex metrics.

The color-coded indications also serve an important role in alerting supervisors when an HCP's vitals reach concerning thresholds. Supervisors can review this data and determine whether intervention is necessary. For instance, if the app indicates sustained high stress or irregular heart rate, it may suggest that the supervisor temporarily relieve the HCP of their duties to prevent burnout or medical complications. This feature ensures that the app can be used as a proactive tool for preventing occupational stress-related

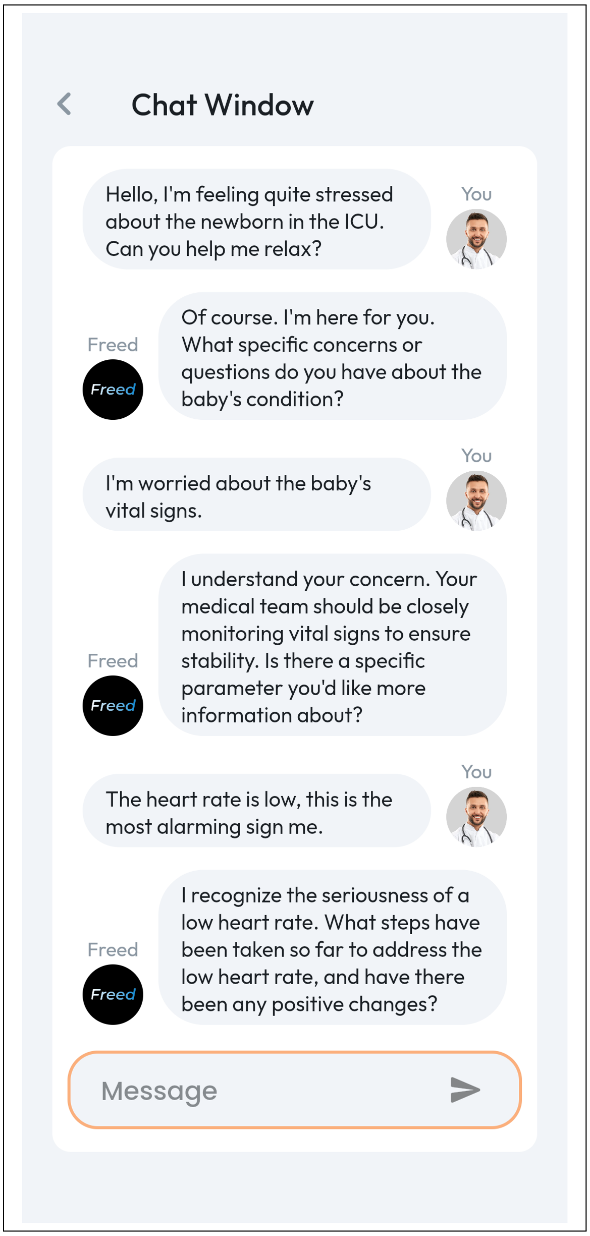

Figure 26: Chat Window

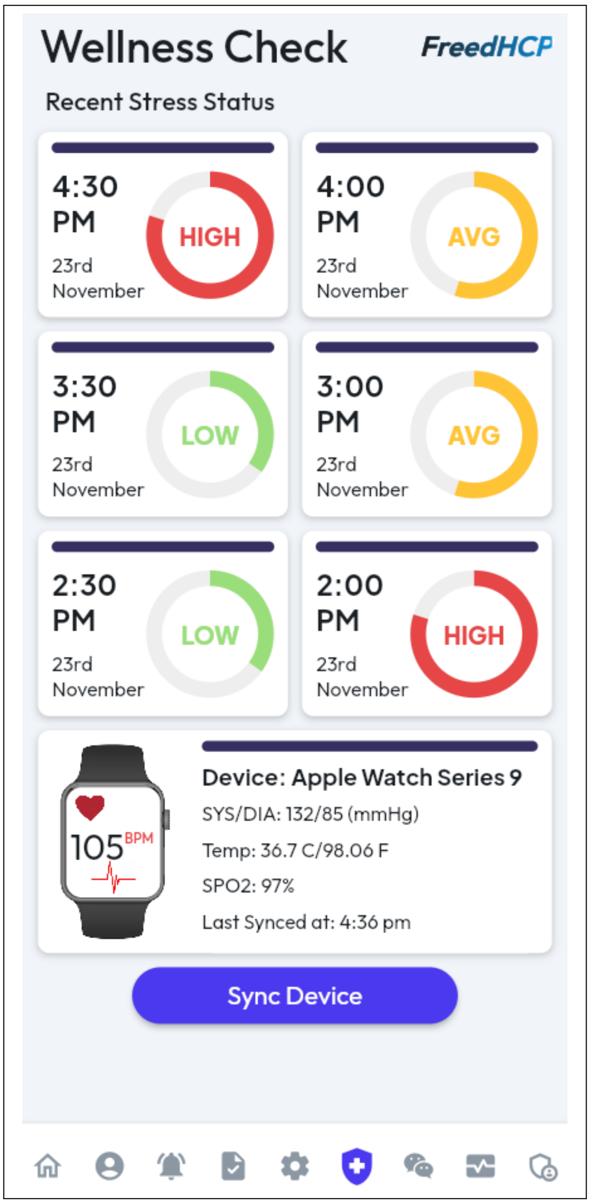

Figure 27: Wellness Check

issues, offering both HCPs and their supervisors a way to manage health more effectively in real time.

4.2.5 Supervisor Dashboard

The ‘Supervisor Dashboard’ offers supervisors a comprehensive view of the HCPs under their supervision, providing them with the necessary tools to monitor and assess the well-being of their staff in real time. This dashboard allows supervisors to oversee detailed health metrics and conditions for each HCP, focusing particularly on stress levels. By providing a graphical representation of each HCP’s average stress levels over the last 7 days, as demonstrated in Figure 29, supervisors can easily track trends and fluctuations in stress, helping them to quickly identify personnel who may be experiencing heightened or prolonged stress.

This data-driven approach allows supervisors to make informed decisions about how to best manage their teams. For example, if a supervisor notices consistently high stress

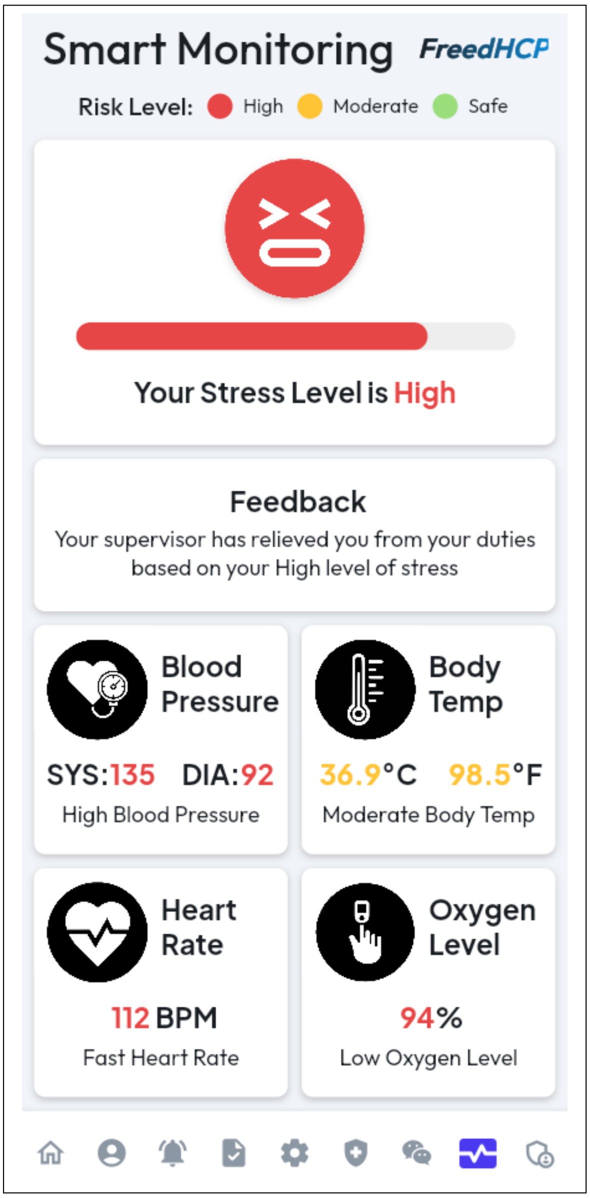

Figure 28: Smart Monitoring

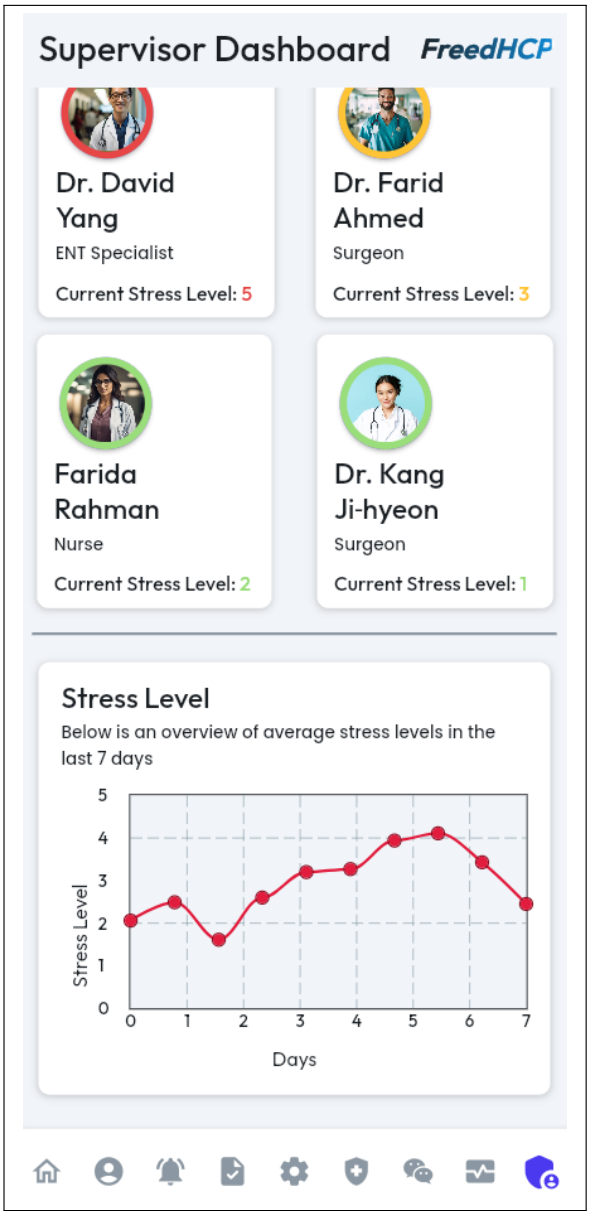

Figure 29: Admin Dashboard

levels for a particular HCP, they can take preemptive measures, such as temporarily relieving that individual from duty, providing additional support, or offering time for recovery to prevent burnout. By viewing stress levels in a visual format, supervisors can more easily identify patterns that might otherwise go unnoticed.

5 Usability Evaluation

5.1 Study Design

We conducted an evaluation of the FreedHCP app prototype using a cross-sectional survey to gather quantitative feedback from participants. Each participant received a PDF containing a link to the app prototype and a Google Form survey. After exploring the prototype, participants completed the survey, which took approximately 10 minutes.

The survey began with an overview of the study and included a consent form to ensure ethical compliance. Participants then provided demographic information such as gender, age range, and work setting. Following this, they assessed the app's usability using the SUS [12] questionnaire.

Additionally, two questions were asked to determine the most liked feature of the app and participants' willingness to use it, as well as whether they would recommend it to others (responses were collected using 'yes', 'no', and 'maybe' options). These questions helped measure the perceived usefulness of the app and the likelihood of adoption by HCPs.

The study spanned two weeks in March 2024, during which participants could complete the evaluation at their convenience within the provided timeframe.

5.2 Participants

The prototype and survey links (in a Portable Document Format (PDF)) were distributed to mailing lists of HCPs working in various hospitals and medical universities within our local state. Participants were required to meet two inclusion criteria:

1. A basic understanding of the English language, as the prototype was developed in English, and
2. Basic knowledge of smartphone and smartwatch operations.

Participation was entirely voluntary, and no incentives were provided for completing the survey. All participants were expected to interact with the full range of features available in the prototype.

Our recruitment effort resulted in 24 responses, where 45.8% (n=11) of the participants were females. Respondents ranged in age from 18 to 64 years, with an average age of 33.08 years (SD 8.07). The age distribution was as follows: 4 participants (18-24 years), 15 participants (25-34 years), 3 participants (35-44 years), 1 participant (45-54 years), and 1 participant (55-64 years).

In terms of professional background, 66.7% (n=16) of the participants were physicians (doctors), while 33.3% (n=8) were medical students. This participant demographic provided valuable feedback on the prototype's usability and perceived effectiveness, aiding in understanding the feasibility of the 'FreedHCP' app for stress management in healthcare settings.

5.3 Measures and Data Analysis

For the evaluation of the developed FreedHCP app, we utilized SUS, a widely used tool for assessing the perceived usability of various products and systems. Reports indicate that SUS has been utilized in approximately 43% of usability studies, emphasizing its prevalence [58]. The SUS consists of a concise 10-item questionnaire, which alternates between positive and negative statements to help mitigate potential response biases. Participants rate each item using a five-point Likert scale, ranging from 'strongly disagree' to 'strongly agree'.

To calculate the final usability score, which ranges from 0 to 100, all 10 items must be completed, with necessary adjustments made for any unrated items. This score provides a grade, ranging from A (adjective rating 'Excellent') to F (adjective rating 'Awful'), offering a comprehensive evaluation of the system's usability.

For data analysis, Microsoft Excel was used to calculate descriptive statistics, including the mean values, standard deviations (SDs), percentages, and frequency distributions. These metrics helped us interpret the participants' feedback and overall evaluation of the app's usability and perceived effectiveness.

5.4 Findings

5.4.1 SUS Score (RQ3: How do HCPs in Bangladesh perceive the usability of the proposed mHealth app for workplace stress management?)

The system's usability analysis, based on the collected data, reveals a mean SUS score of 71.77 (median = 75, SD = 14.85). This score indicates favorable usability, surpassing the marginal usability threshold of 68. The median score of 75 suggests that at least half of the participants rated the system's usability above this value, highlighting a generally positive reception of the system.

The standard deviation of 14.85 points to moderate variability in user perceptions. While many users rated the system highly, some users gave lower ratings, which suggests potential areas for improvement. Despite this variability, the adjective rating for the mean SUS score of 71.77 classifies the system as 'Good'. This aligns with the overall quantitative data, confirming that the system's usability is effective and user-friendly.

Additionally, the system has been graded as 'B' on the usability grading scale. In this context, a grade of B signifies that the system is 'Good' and generally acceptable but not 'Excellent'. The acceptability rating of 'Good' complements the other metrics, reinforcing the conclusion that the system was well-received by the majority of users.

Table 5.1 displays the average SUS score for each individual question. Figure 30 shows the participants' vote distribution on the 5-point Likert scales for each SUS item, and Figure 31 visually represents the overall SUS study score and usability ratings. These figures provide further insights into user experiences and highlight areas of the system that were particularly well-received or in need of improvement.

Table 5.1: Average SUS scores

SL	SUS Item	Mean Score (SD)
1	I think that I would like to use this app frequently.	3.88 (0.93)
2	I found the app unnecessarily complex.	2.5 (1.19)
3	I thought the app was easy to use.	4.21 (0.76)
4	I think that I would need the support of a technical person to be able to use this app.	1.96 (1.02)
5	I found the various functions in the app were well integrated.	4.0 (0.91)
6	I thought there was too much inconsistency in this app.	2.17 (1.11)
7	I would imagine that most people would learn to use this app very quickly.	3.79 (1.04)
8	I found the app very clumsy to use.	1.92 (1.19)
9	I felt very confident using the app.	3.92 (0.91)
10	I needed to learn a lot of things before I could get going with this app.	2.54 (1.44)
	Overall Mean SUS Score	**71.77 (14.85)**

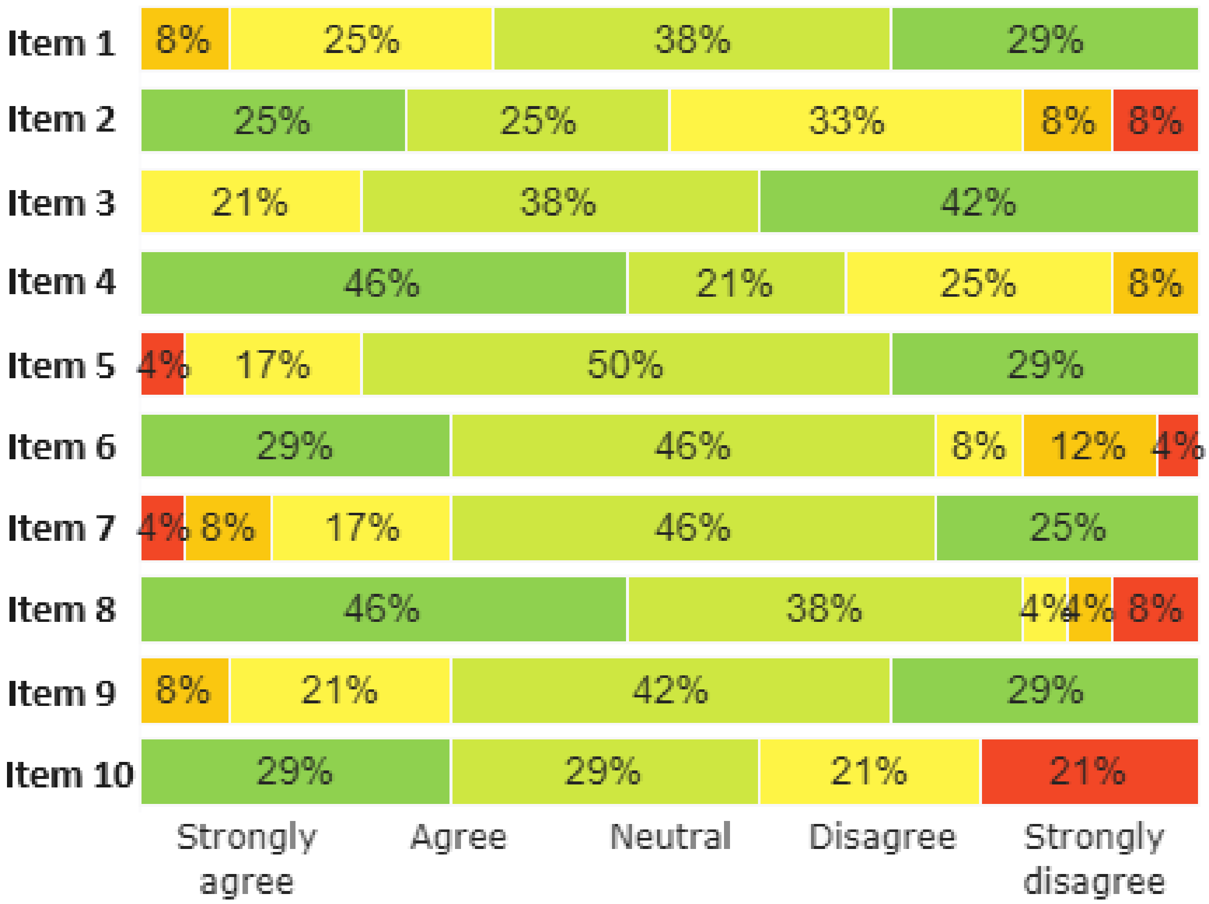

Figure 30: Participant voting on 5-point Likert scales for individual SUS items (Generated using [12])

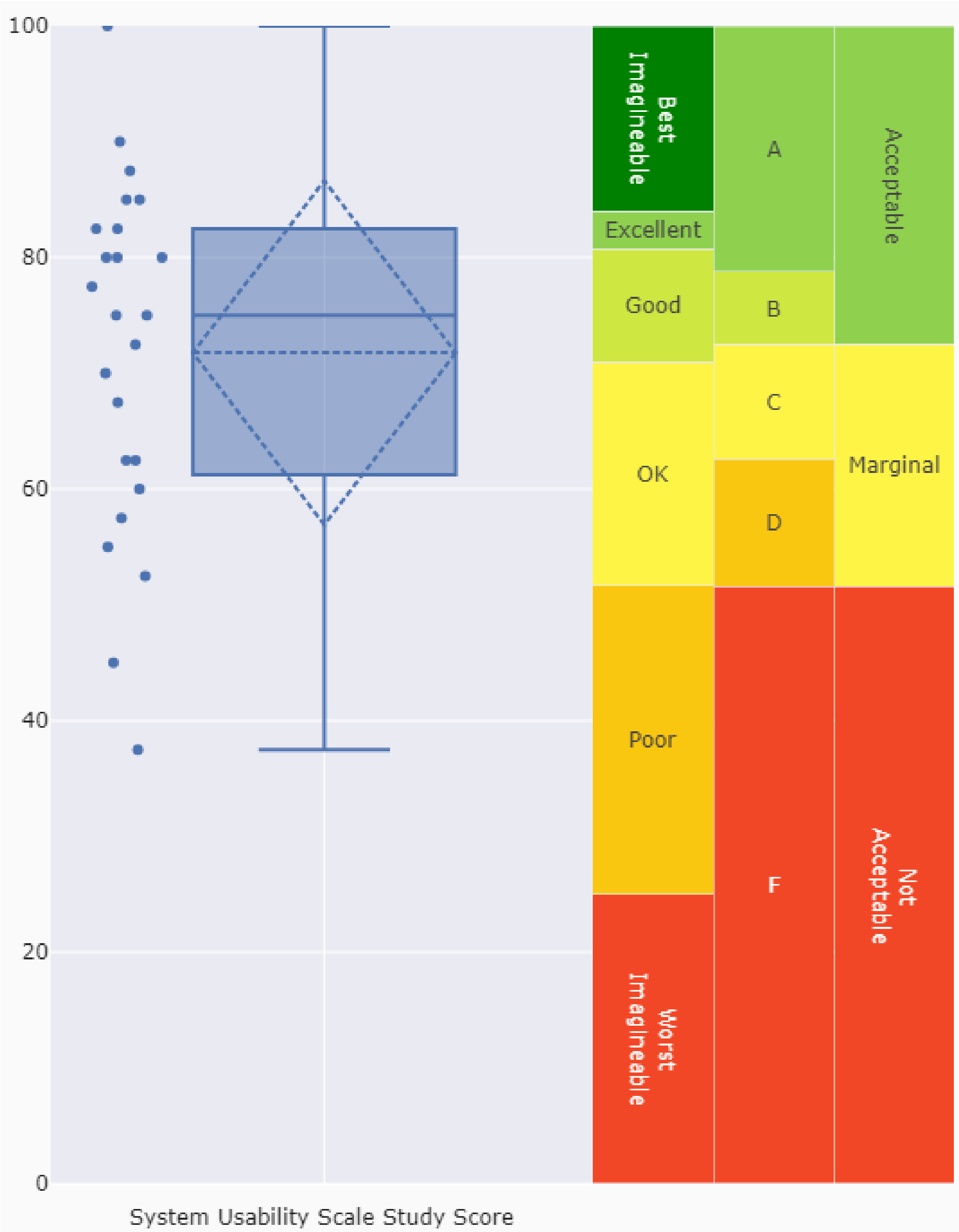

Figure 31: SUS study score (Generated using [12])

5.4.2 Popularity of Features

The ‘Smart Monitoring’ feature from the ‘Wellness Check’ category emerged as the most popular feature among participants, receiving 29.2% of the votes. The ‘Get Help’ feature was the second most favored, with 12.6% of the votes, followed closely by the ‘Notification Settings’ feature, which received 12.5% of the votes. Ranking fourth, the ‘Supervisor Dashboard’ feature received 4.2% of the votes. Additionally, 8.4% of participants selected features outside of the provided categories, indicating an interest in other functionalities not highlighted in the survey. These findings suggest that Smart Monitoring and support-related features are highly valued by users for stress management.

5.4.3 Willingness to Use and Recommend (RQ2 : Evaluation Study Phase)

Out of 24 participants, 95.8% expressed that they were willing to use the app at their workplace and would like to recommend it to their colleagues and peers. Only 4.2% declined to use the app and nobody was neutral regarding this question.

Out of the 24 participants, an overwhelming 95.8% expressed their willingness to use the FreedHCP app at their workplace and indicated that they would recommend it to their colleagues and peers. Only 4.2% of participants declined to use the app, while no one remained neutral regarding this question. This is shown in the Figure 32. This strong

Figure 32: Willingness to Use the Proposed App Based on Number of Participants

approval suggests a high level of perceived usefulness and a positive reception among HCPs, highlighting the app’s potential for widespread adoption in managing workplace stress.

6 Automated Stress Detection among Medical Students

This chapter explores ML and DL-based approaches for screening anxiety, depression, and burnout among medical students. Various models, such as an Ensemble classifier combining Random Forest (RF), Naive Bayes (NB), and Light Gradient-Boosting Machine (LightGBM), were compared with a DNN. The DNN consistently outperformed the ensemble classifier across all target variables, achieving accuracies of 81.4%, 76.65%, and 73.59% for Center for Epidemiologic Studies Depression (CESD), Maslach's Burnout Inventory (MBI), and State and Trait Anxiety Inventory (STAI), respectively. Feature importance analysis using Information Gain (IG), training vs. validation accuracy and loss plots, and ROC curves further demonstrated the DNN's superior performance, with micro-average AUC scores of 77%, 73%, and 90% compared to the ensemble classifier's 68%, 61%, and 75% for CESD, MBI, and STAI, respectively.

These findings pave the way for developing a DL-based, efficient, and automated stress detection method that could be integrated into the backend of a fully functional stress management app for HCPs. This approach holds promise for future implementations, ultimately enhancing better stress management and providing much-needed mHealth based support to HCPs.

6.1 Background and Related Works

Nearly 1 billion people worldwide live with a mental disorder [35]. Mental health issues such as anxiety, desperation, and burnout severely impact both personal and professional lives, often leading to decreased productivity, strained relationships, and a general decline in quality of life. Medical students are particularly vulnerable, experiencing higher rates of depression, anxiety, and burnout compared to their non-medical peers, with prevalence rates of 27% and 34% for depression and anxiety, respectively [68]. These issues intensify during critical transitional periods such as the entering year, transfer to clinical training, and the final year before residency [68], as students face the dual challenge of mastering complex material and managing patient care in a high-pressure environment. Untreated, these mental health concerns can negatively affect students' health, academic performance, and future careers.

Despite their heightened risk, medical students often lack adequate training in accessing mental health resources [68]. Traditional screening methods like self-reported questionnaires and clinician interviews face barriers such as stigma, lack of awareness, and reluctance to seek help. This gap emphasizes the critical need for automated, unbiased, and discreet screening equipment with early detection and intervention capabilities. Automated tools offer a promising solution by ensuring confidentiality and scalability, allowing for the identification of subtle patterns that lead to more complex evaluations [10]. Early detection through AI and ML-driven methods can provide timely interventions, particularly in high-risk groups such as medical students.

Recent advancements in AI, particularly DL, have shown great promise in the field of automated mental health screening [10]. DL methods can analyze data sources like text, speech, and physiological signals to detect mental health conditions such as depression, anxiety, and burnout with high accuracy. Studies such as [13, 66, 52, 50, 54] have demonstrated the effectiveness of these approaches in accurately predicting conditions like depression, anxiety disorders, and burnout, highlighting the potential for AI-driven tools to bridge the gap between untreated mental health issues and professional help.

A stacking ensemble approach using DL architectures was proposed in [13] for automatic identification of depression, anxiety, and their comorbidity using the Self Reported Mental Health Diagnoses (SMHD) dataset that contains textual data of Reddit users who are labeled with one or more mental health conditions. Their proposed stacking comprises two layers. The lower layer uses a Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), or a hybrid network of CNN and LSTM-based base classifiers for single-label classification. In contrast, the upper layer employs a Dense Neural Network for multi-label classification by utilizing the results of base classifiers. They carried out numerous combinations of classifiers and claimed that CNN-based classifiers performed the best, with an F1 score of around 79%, for identifying users with a single target condition (depression, anxiety, or comorbidity).

Authors in [5] collected user-generated textual data from three publicly available datasets, e.g., CLPsych 2015 Shared Task, Reddit, and eRisk, to detect depression using hybrid and ensemble methods. In their Hybrid methods, they utilized different sentiment lexicons for text classification by applying Logistic Regression (LR). Additionally, LSTM, AttentionLSTM, Hybrid Lexicon-Based LR, and an ensemble of LSTM and Lexicon-Based LR models was employed. They reported that the ensemble of LSTM and Lexicon-based LR achieved the highest accuracy of 75% with an F1 score of 77%.

To develop a predictive model for physician burnout, authors in [59] conducted a monthly survey using the Professional Fulfillment Index (PFI) for six months and collected categorical monthly burnout scores along with EHR audit logs of participants. They employed five ML regressor models including linear regression, Support Vector Machine (SVM), RF, gradient boosting tree, and Multi-Layer Perceptron Neural Network (MLPNN). They compared the performance of the five regressors and found that MLPNN outperformed other regressors with an accuracy of 78.1%.

The study in [27] used the Reddit Self-reported Depression Diagnosis (RSDD) dataset, which includes social media posts from both users with depression diagnoses and control users to predict depression. Four classifiers including LSTM, Attention-LSTM, and Attention-BiLSTM, a proposed X-A-BiLSTM model, which combines Extreme Gradient Boosting (XGBoost) and Attention-BiLSTM. They reported that X-A-BiLSTM model outperformed earlier state-of-the-art models along with the other three models used in this study, by achieving the best results in Precision (69%), Recall (53%), and F1 (60%) for diagnosed users.

6.2 Materials and Methods

6.2.1 Dataset Description

The dataset comprises information about the mental health, empathy, and burnout levels of medical students in Switzerland. In the cross-sectional research [21], 886 medical students from curriculum years 1 through 6 participated. In addition to internal measures which include job satisfaction, psychological distress, academic performance, self-reported health status, and several types of empathy rating scales (e.g., Jefferson scale of empathy, Questionnaire of Cognitive and Affective Empathy (QCAE) cognitive empathy score, QCAE affective empathy score, Ability of Modify Self-Presentation (ASMP) score, CESD score, STAI score, MBI emotional exhaustion score, MBI cynicism score, and MBI academic efficacy score)) [21]. The age range of participants spans from 17 to 49 years old which indicates a broad representation of age groups. The dataset reflects a predominantly French-speaking student body, with 717 participants reporting French as their mother tongue. Other languages with considerably fewer represented groups are German, English, Italian, and Portuguese. Regarding gender, the dataset primarily comprises female participants, with 606 women compared to 275 men and 5 non-binary individuals. The primary objective of curating this dataset was to discern insights into the well-being of medical students with the intent of informing policy enhancements through the explanation of interrelationships among the variables. Consequently, this dataset serves as a valuable resource for identifying potential associations between different feature variables and the mental health outcomes observed among medical students. Empathy dimensions, e.g., cognitive and affective, were assessed using self-report questionnaires and an emotion recognition test. Regression analyses were employed to explore the relationships between empathy dimensions, depressive symptoms, anxiety, and burnout while also considering the influence of curriculum year and gender. With a specific focus on predictive modeling to identify mental health (e.g., depression and anxiety) and burnout levels based on demographic attributes, e.g., age, gender, year of study, self-reported health status, and other variables, this dataset can be used to illuminate the complex interrelation between personal characteristics and psychological well-being among medical students. The specific details of the attributes, including data type and sample range, are presented in Table 6.1.

Table 6.1: Details of the attributes (e.g., type, range) in the dataset

Attributes	**Attribute Details**	**Attribute Type and Range**
id	Participants ID number	String [1 to 886]
age	Age of the participants	Numerical [17-49 years old]
year	Curriculum year	Categorical [1: Bmed1 (245); 2: Bmed2 (135); 3: Bmed3 (143); 4=Mmed1 (123); 5: Mmed2 (127); 6: Mmed3 (113)]
sex	Gender of the participants	Categorical [1: Man (275); 2: Woman (606); 3: Non-binary (5)]

Continued on next page

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Attributes	Attribute Details	Attribute Type and Range
glang	Language speaks (Mother tongue)	Categorical [19 Languages in total (1: French (717); 15: German (31); 20: English (22); 90: Italian (45); 102: Portuguese (27))]
part	Partner status	Categorical [0: No (387); 1: Yes (499)]
job	Job status	Categorical [0: No (577); 1: Yes (309)]
stud_h	Hours of study per week on top of courses	Numerical [0-70 hours]
health	Satisfaction with health status	Categorical [5-point Likert scale]
psyt	Psychotherapy last yer	Categorical [0: No (687); 1: Yes (199)]
jspe	Jefferson scale of empathy	Numerical [67 to 125]
qcae_cog	QCAE cognitive empathy score	Numerical [37-76]
qcae_aff	QCAE affective empathy score	Numerical [18-48]
amsp	AMSP score	Numerical [6 to 35]
erec_mean	Mean empathy score (cognitive & affective)	Numerical [0.35-0.95]
cesd	CESD score	Numerical [0-56]
stai_t	STAI score	Numerical [20-77]
mbi_ex	MBI Emotional Exhaustion	Numerical [5-30]
mbi_cy	MBI Cynicism	Numerical [4-24]
mbi_ea	MBI Academic Efficacy	Numerical [10-36]

6.2.2 Data Pre-processing

To ensure the integrity and reliability of subsequent analyses, data pre-processing is a key phase. The dataset in this study was pre-processed using the following methods: data transformation, cleaning, and the elimination of outliers. The initial phase of data pre-processing involved identifying missing values and duplicate entries. The analysis exhibited no instances of missing values or duplicate entries. Afterwards, a data transformation technique was applied to standardize the features. Ordinal features, e.g., age, study hours, and various empathy scores (e.g., Jefferson scale of empathy, QCAE cognitive empathy score, QCAE affective empathy score, AMSP score), were normalized using the min-max scaler. This process involves scaling the values of these features to a standardized range between 0 to 1. The presence of outliers in a dataset leads to a considerable challenge, potentially skewing analytical results and undermining the effectiveness of ML models [70]. To address these concerns, the Isolation Forest algorithm was employed for its efficacy in identifying and isolating anomalous data points [43]. With a specified contamination value of 0.1, the Isolation Forest algorithm detected six outliers. The outliers were eliminated to reduce their adverse effect on analytical outcomes.

6.2.3 Dataset Labeling

The data labeling process involved categorizing the continuous score values of three psychological assessment instruments, CESD, STAI, and MBI (mean), into distinct classes. These classes were predetermined based on established thresholds proposed by prior studies [65, 2, 51]. For the CESD scores, participants were categorized into four classes in terms of depression: Not depressed, Mildly depressed, Moderately depressed, and Severely depressed. Similarly, the STAI scores were divided into three classes: No or low anxiety, Moderate anxiety, and High anxiety. Lastly, the MBI scores were classified into three categories: Low burnout and moderate burnout. The detailed classification of CESD, STAI, and MBI scores with the number of corresponding instances available in the dataset is presented in Table 6.2.

This data labeling technique complies with established standards in psychological research which makes it more straightforward for later classification-based predictive analysis. The class distribution of the three target variables (CESD, MBI (mean), and STAI) are mentioned respectively. In this context, the distribution of classes in the MBI label exhibits a significant imbalance ratio. Because it is primarily attributable to the lower

Table 6.2: Classification of CESD, STAI, and MBI Scores with number of corresponding instances available in the dataset

Category	**Classification**	**Count**
Depression (CESD)	Not depressed (scores 0-9)	234
	Mildly depressed (scores 10-15)	187
	Moderately depressed (scores 16-24)	221
	Severely depressed (scores > 25)	238
Anxiety (STAI)	No or low anxiety (scores 20-37)	301
	Moderate anxiety (scores 30-44)	184
	High anxiety (scores 45-80)	395
Burnout (MBI)	Low burnout (scores < 17)	500
	Moderate burnout (scores 18-29)	376
	High burnout (scores > 36)	4

representation of the 'High burnout' class compared to the other two classes (e.g., 'Low burnout' and 'Moderate burnout').

6.2.4 Model Selection and Development

In this section, the selection and development of two distinct classification models are presented which were applied to analyze psychological assessment data. The first model, a DNN, is featured by its capacity to capture intricate patterns within the data [63]. The second model is an Ensemble Classifier comprising RF, LightGBM, and NB algorithms. These algorithms were chosen for their diverse advantageous characteristics. Each subsection provides into the details of the model architecture, optimization techniques, and rationale behind their selection.

Deep Neural Network (DNN)

The DNN comprised an input layer with 12 neurons, followed by two hidden layers with 10 and 8 neurons, respectively. The output layer consisted of 3 neurons, corresponding to the multiclass classification task. To facilitate multiclass classification, the output layer was activated by the softmax function, while Rectified Linear Unit (ReLU) activation functions were applied to the hidden layers [63]. The DNN was optimized using the Adam optimizer, and 'categorical cross-entropy' was employed as the loss function to measure the disparity between predicted and actual class labels [63]. Because of the multi-layered architecture, DNN is adept at identifying convoluted patterns and correlations within data [63]. This enables it to find variations and multifaceted relationships that might not be seen using traditional methods.

Ensemble Classifier

Ensemble classifier amalgamates the predictions from multiple base classifiers to produce a consolidated and robust classification outcome [55]. The RF, LightGBM, and NB algorithms have been implemented in the ensemble classifier. RF is recognized for its tolerance against overfitting and its efficacious handling of high-dimensional data [60]. It reduces the risk of model variation by building multiple Decision Trees (DTs) and combining their predictions. LightGBM stands out for its efficient training speed [80]. By using a gradient boosting framework, LightGBM sequentially builds DTs [80]. This technique results in improved model convergence [80]. NB classifier is simple and computationally efficient [53]. Despite its underlying assumption of feature independence, NB often yields competitive performance [53].

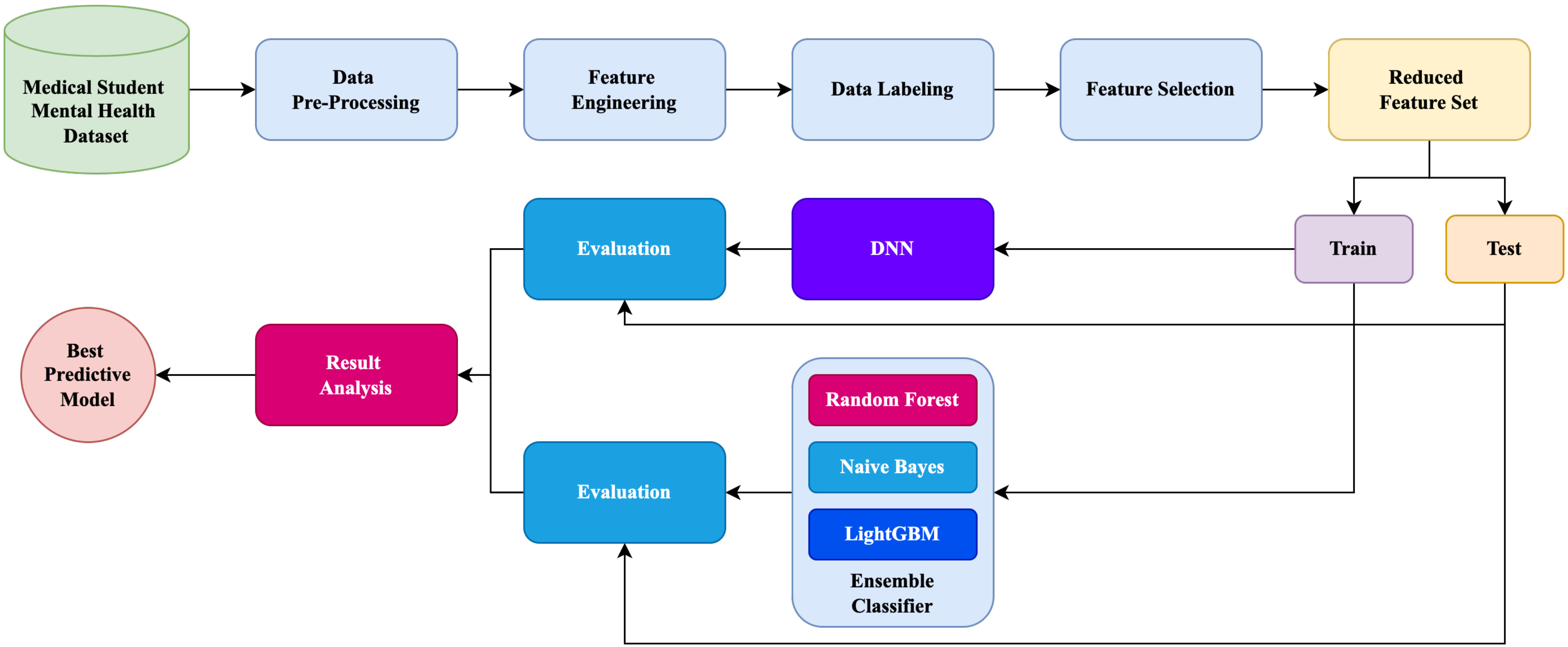


Figure 33: Diagram of proposed methodology followed in this work

6.2.5 Feature Engineering

Three attributes, sharing the same scale, related to MBI, namely 'mbi_ex' (MBI Emotional Exhaustion), 'mbi_cy' (MBI Cynicism), and 'mbi_ea' (MBI Academic Efficacy), were used to create a new feature termed 'MBI (mean)'. This new feature encapsulates the mean value of the aforementioned MBI attributes (participant-wise). This was done on purpose in order to meet one of the goals by synthesizing an accurate representation of burnout and using it as a target variable for predictive analysis. Additionally, the 'id' feature, denoting participant serial numbers, was removed from the dataset to eliminate potential bias. This step ensured that the models did not inadvertently learn spurious correlations associated with participant identifiers.

6.2.6 Feature Selection

Feature selection techniques aim at identifying the most informative attributes or features that contribute to the prediction of target variables. In this study, feature selection was conducted using the IG method to determine the importance of features in predicting three distinct target variables: STAI, CESD, and MBI. IG was chosen for its ability to quantify the relevance of features based on their contribution to reducing uncertainty in classification tasks. IG is well-suited for multiclass classification tasks. Moreover, it provides transparent and interpretable results. IG is computationally efficient. Therefore, it is feasible to analyze datasets with a large number of features.

6.2.7 Ablation Study

An ablation study in the context of ML and DL is a systematic approach to comprehend the contribution of each component of a model to its overall performance. By ablating or removing specific parts of the model, e.g., layers, neurons, or number of epochs etc. and then obeserve the impact on performance. Researchers can gain insights into which aspects of the model are most critical to its success. In DL, this might involve simplifying the architecture of a neural network or omitting certain data inputs or transformations. The goal is to identify which elements of the model are necessary for maintaining high performance, and which may be superfluous or even detrimental. Ablation studies can lead to more efficient models by streamlining them to retain only the most influential components. In this study, the ablation involved varying the number the hidden layers of the DNN model. This type of modification can reveal how the model's capacity to capture data complexities and generalize from the training data is affected by its size and depth. For the ensemble classifier, the ablation study was carried out by altering between different classifiers within the ensemble.

6.2.8 Evaluation Metrics

Classification metrics are essential since they provide useful insights into how well classification algorithms are performing in terms of predicting unseen data. Furthermore, classification metrics allow it to be easier to compare several methodologies and models. The classifiers in this study will be evaluated using the following classification metrics: MCC, ROC-AUC, accuracy, precision, and recall.

Accuracy

Accuracy is easy to calculate and one of the popular metrics in classification tasks. Accuracy measures how accurately the model performed compared to all data that represent the correct prediction. If model results are classified as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The formula for calculating accuracy is as stated below [46]:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.1}$$

Precision

Precision represents how accurately the model classified TP data compared to all the positive predictions which represents TPs among all the position predictions. A model with high precision means, the model is good at classifying positive class data and low precision means the model predicts more FP. The formula to calculate precision is as stated below [46]:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6.2}$$

Recall

Recall, also known as sensitivity, quantifies the model's ability to correctly identify TP cases among all actual positive instances in the dataset. It assesses the model's ability to capture all true positive cases and avoid FN, which are positive cases misclassified as negative. The formula to calculate the recall is as stated below [46]:

$$\text{Recall or Sensitivity} = \frac{TP}{TP + FN} \tag{6.3}$$

Matthews Correlation Coefficient (MCC)

MCC is a correlation coefficient between the observed and predicted binary classifications. It ranges from -1 to 1, where 1 indicates perfect prediction, 0 indicates random prediction, and -1 indicates total disagreement between prediction and observation. The formula to calculate MCC is as stated below [26]:

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{\begin{array}{c}(\text{TP} + \text{FP}) \times (\text{TP} + \text{FN}) \\ \times (\text{TN} + \text{FP}) \times (\text{TN} + \text{FN})\end{array}}} \tag{6.4}$$

Receiver Operating Characteristic Area Under the Curve (ROC-AUC)

ROC-AUC quantifies the classifier's ability to distinguish between classes. It represents the area under the Receiver Operating Characteristic curve, which plots the true positive rate against the false positive rate. The formula to calculate ROC-AUC is as stated below [15]:

$$ROC - AUC = \int_0^1 \text{TPR}(\text{FPR}) d(\text{FPR}) \tag{6.5}$$

where, TPR = True Positive Rate, and FPR = False Positive Rate.

6.2.9 Experimental Setup

For the experiment, the following hardware setup was used: CPU: Intel Core i7 @4.2GHz, Primary Memory/RAM: 64GB, Graphics Card: Nvidia RTX 4060Ti, Secondary Memory/Storage: 1TB Solid. State Drive. This hardware configuration provided sufficient computational resources to execute the necessary data analysis, model training, and evaluation tasks. In addition to the hardware setup, a suite of software programs and Python packages were used. These include: Python programming language, Spyder in Anaconda Navigator, TensorFlow, Numpy, Seaborn, KERAS, and Scikit Learn [81].

6.3 Experimental Results and Analysis

6.3.1 Comparison Between Learning Methods

For each target variable, the Ensemble Classifier achieved at least 60% or higher for all of the evaluation metrics, while DNN secured more than 71%. Overall, DNN outperformed Ensemble Classifier by achieving accuracies of 81.49%, 76.65%, and 73.59% for STAI, CESD, and MBI respectively. Precision, Recall, MCC, and AUC of Ensemble Classifier and DNN for the target variables are shown in Table 6.3 in details. Both Ensemble Classifier and DNN individually performed the best for STAI, achieving accuracies of 75.8% and 81.49%. However in comparison to STAI, the performance of Ensemble Classifier significantly drops for both CESD (accuracy = 67.05%) and MBI (accuracy = 60.82%), while DNN follows a similar trend by performing poorly for CESD (accuracy = 76.65%) and MBI (accuracy = 73.59%) as these are selected as the target variable. The overall best performance is displayed by DNN with STAI as the target variable, as it achieves an accuracy of 81.49%, precision of 79.1%, recall of 80.97%, MCC score of 79.52%, and AUC score of 81%.

6.3.2 Feature Importance and Individual Variability

IG was employed to identify key variables that contribute most to the predictive capabilities of both models. Detailed results about important features for predicting MBI is shown in Fig. 34-a which includes Hours of Study per Week (stud-H) that displayed the highest importance with a score of more than 0.025, CES-D total score (cesd_label) with score of around 0.020, mean value of correct responses (erec_mean) with score of around 0.010, along with other features that contributed in varying proportions. Some of the features did not show any relevance at all which includes Age at Questionnaire 20-21 (age), QCAE Affective empathy score (qcae_aff), Partnership Status (part) etc.

Table 6.3: Performance comparison of Ensemble classifier and DNN in terms of the classification metrics

Classifier	Label	Accuracy (%)	Precision (%)	Recall (%)	MCC (%)	AUC (%)
Ensemble Classifier	STAI	75.8	73.51	73.97	74.89	75
	CESD	67.05	66.83	66.41	65.45	68
	MBI	60.82	60.08	60.24	60.32	61
DNN	STAI	**81.49**	**79.1**	**80.97**	**79.52**	**81**
	CESD	76.65	75.98	76.27	76.04	77
	MBI	73.59	72.83	71.55	72.7	73

The important features for the target variable CESD are displayed in Fig. 34-b. STAI score (stai_t) exhibits the highest importance, which is over 0.25. Additional features including Satisfaction with Health (health), Age, and Curriculum Year (year), and JSPE total empathy score (jspe) exhibits far less importance in comparison to STAI score. QCAE Affective Empathy Score and Mother Tongue (glang) does not exhibit any importance at all.

With STAI as the target variable shown in Fig. 34-c, cesd_label showed the highest importance with a score greater than 0.20. Other features such as QCAE Affective Empathy Score, Having a Job (job) reached almost a score of 0.05, while the rest such as Gender (sex), health, Psychotherapy Last Year (psyt) showed minuscule reading which is lower than 0.05.

6.3.3 Training Vs. Validation Accuracy and Loss

The presented training vs validation accuracy and loss plots in Fig. 35 represent the performance of a DNN for three different target variables. The DNN was trained for 20 epochs for all three target variables. It is observed that both training and validation accuracy improve over epochs. It indicates that the DNN model is learning and able to generalize from the training data to unseen data. This is a positive sign of model effectiveness. Similarly, the training and validation loss decrease over epochs showing that the model's predictions are becoming closer to the actual values.

The MBI accuracy plot in Fig. 35-a demonstrates a steady increase in both training and validation accuracy with a small gap between them. This small gap suggests that the model is not overfitting. Overfitting is when a model performs well on the training data but poorly on new, unseen data. However, the loss plot in Fig. 35-d for MBI shows a sharp decline initially leveling off as epochs increase. The validation loss closely follows the training loss which indicates a good fit.

The STAI accuracy plot in Fig. 35-b shows the closest convergence between training and validation accuracy. It suggests a balanced learning and a model that generalizes well. This is an ideal scenario that the model is learning representations that are equally applicable to both the training and validation datasets. The loss plot in Fig. 35-e for STAI also reflects a good fit with both training and validation loss decreasing and stabilizing in a tight band.

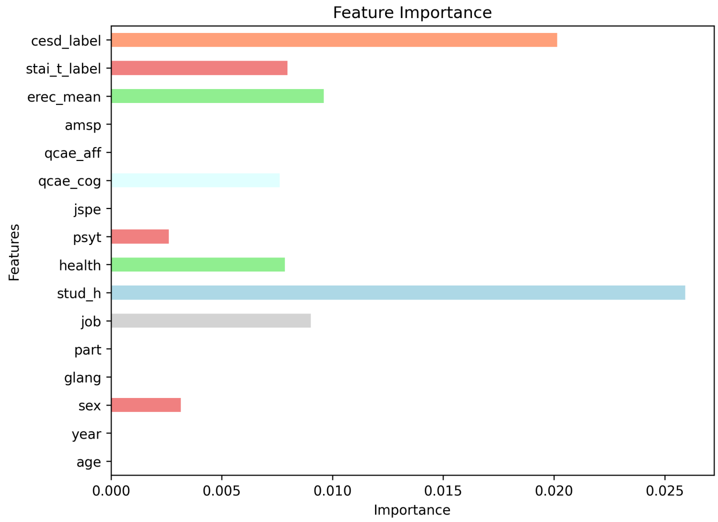
For CESD, the accuracy plot in Fig. 35-c indicates that the validation accuracy surpasses the training accuracy as in the beginning which indicates a potential underfitting. But, after 4th epoch, it maintains a balanced gap between them. However, the MBI loss plot in Fig. 35-f echoes this observation, with training loss continuing to decrease while validation loss begins to plateau which also reflects a good fit.

The close performance between training and validation sets across all target variables suggests that the DNN architecture is well-suited for this multiclass classification task. The consistent decrease in loss demonstrate that the model's learning is stable and effective over a range of epochs.

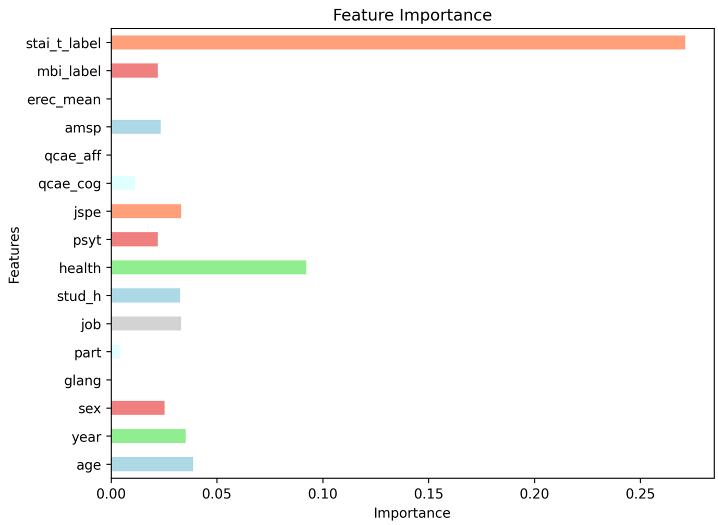
6.3.4 ROC-AUC

The performances of both Ensemble Classifier and DNN for CESD, MBI, and STAI is shown using The ROC curves displayed in Fig. 36.

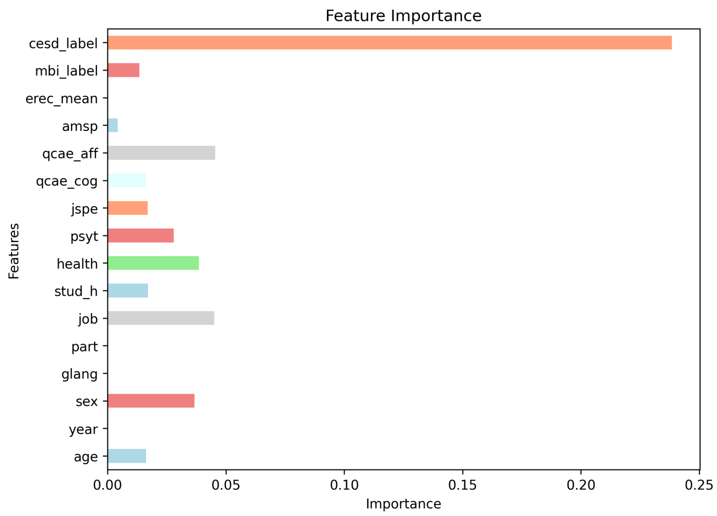
The performance of DNN for identifying depression using CESD as target variable is shown in Fig. 36-a. The AUC scores for class 0, class 1, class 2, and class 3 are 83%, 86%, 61%, and 83% respectively, which indicates good classification performance for majority



(a)

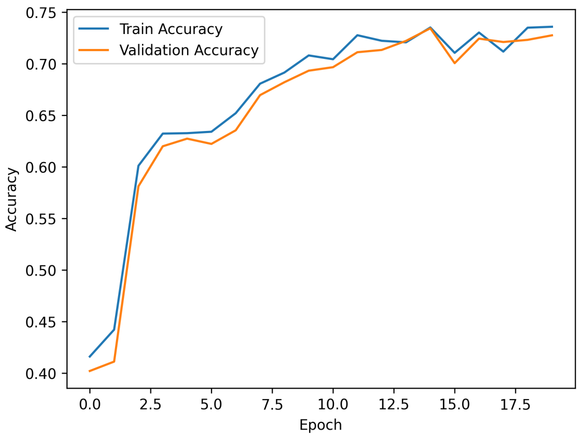


(b)

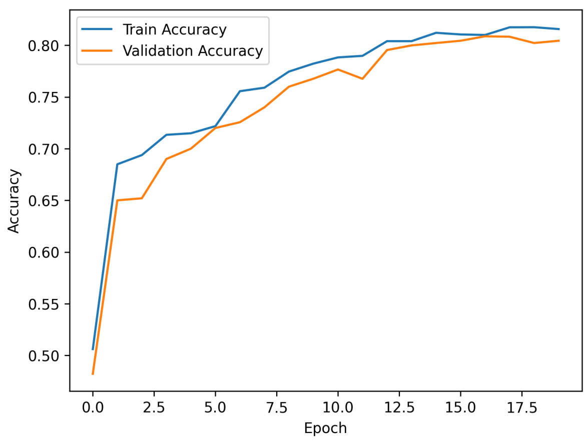


(c)

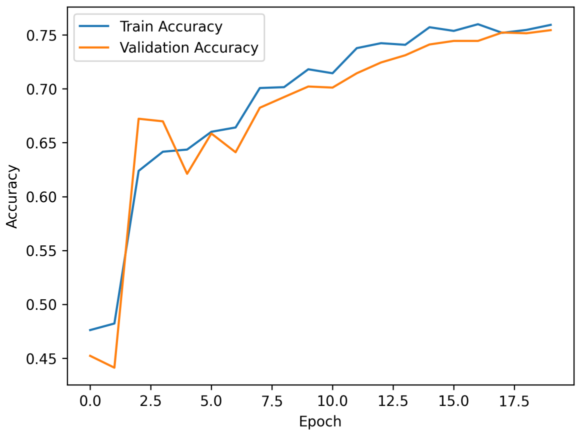
Figure 34: Feature importance assessment using IG with- (a) MBI as the target variable (b) CESD as the target variable, and (c) STAI as the target variable



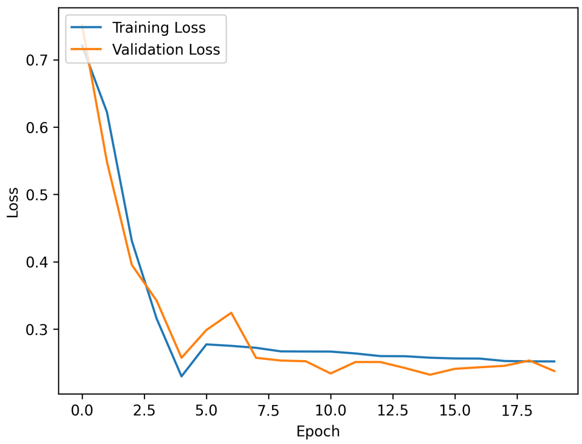
(a) DNN on MBI



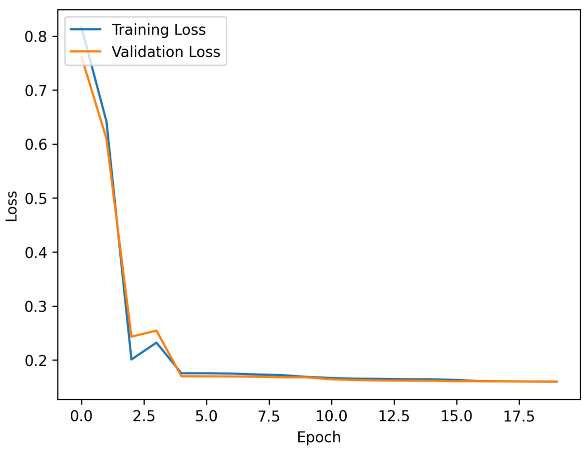
(b) DNN on STAI



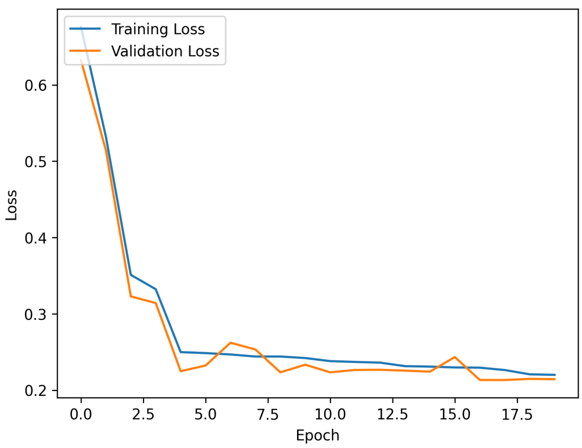
(c) DNN on CESD



(d) DNN on MBI



(e) DNN on STAI



(f) DNN on CESD

Figure 35: (a) Training accuracy vs. validation accuracy of DNN on target variable MBI; (b) Training accuracy vs. validation accuracy of DNN on target variable STAI; (c) Training accuracy vs. validation accuracy of DNN on target variable CESD; (d) Training loss vs. validation loss of DNN on target variable MBI; (e) Training loss vs. validation loss of DNN on target variable STAI; and (f) Training loss vs. validation loss of DNN on target variable CESD

of the classes except for class 2. The micro-average ROC curve (overall performance across all class) with an AUC score of 77% suggests that DNN achieved overall good classification performance across all class for CESD.

ROC curves shown in Fig. 36-b is used to display the performance of DNN to identify burnout using MBI as the target variable. The highest classification performance is achieved for class 2 with an AUC score of 87%, while the next best performance is achieved for class 1 with an AUC score of 85%, indicating good performances for both class. However, the performance is significantly poor for class 0 with an AUC score of 67%. The overall classification performance is good across all class for MBI as indicated by an AUC score of 73% for the micro-average ROC curve.

Out of the three target variables, DNN achieved the best overall classification performance using STAI as the target variable for identifying anxiety with an AUC score of 90% for the micro-average ROC curve. All three classes, DNN achieved AUC scores of more than 83% while for class 1 and class 2 it achieved AUC scores of 91% and 94% respectively.

The ROC curves signifies poor performance for the Ensemble Classifier in comparison to DNN. Ensemble Classifier achieved micro-average AUC scores of 68%, 61%, and 75% for CESD, MBI, and STAI respectively. For Ensemble Classifier, predictions for class 1 of the CESD target variable along with class 1 and 2 of the STAI target variable achieved AUC score of 80% or more. As shown in Fig 36d-f, predictions for rest of the classes fall below 80% when Ensemble Classifier is used.

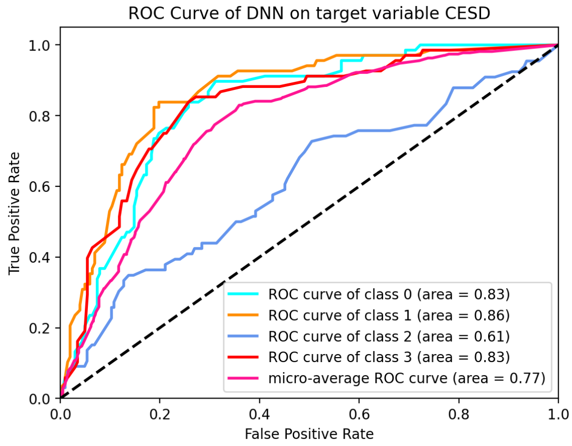
6.3.5 Result of the Ablation Study

The ablation study's findings reveal differences in performance metrics as a result of variations in the architecture of the DNN and configurations of an Ensemble Classifier. The DNN model showed an increase in performance metrics with the addition of more hidden layers peaking at two layers for the STAI target variable. However, adding more than two layers did not significantly improve performance. In fact, there was a slight decrease in performance. For CESD and MBI, the model also performed best with two hidden layers. It demonstrates that for this particular dataset and set of problems, a two-layer architecture provides the most balanced and optimal structure for the DNN model. Table 6.4 presents the results of the ablation study for DNN with different numbers of hidden layers.

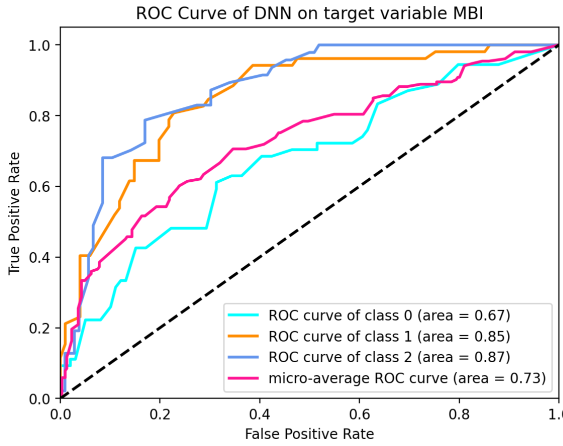
In the Ensemble Classifier configurations, the combination of RF, LightGBM, and NB classifiers provided the highest performance across all metrics for the STAI label. This ensemble configuration outperformed individual RF, NB, and combined RF with LightGBM, or NB with LightGBM. Similar trends were observed for CESD and MBI, although the performance boost was less pronounced than for STAI. Table 6.5 presents the results of the ablation study for Ensemble with different configurations of classifiers.

6.3.6 Threats to Validity

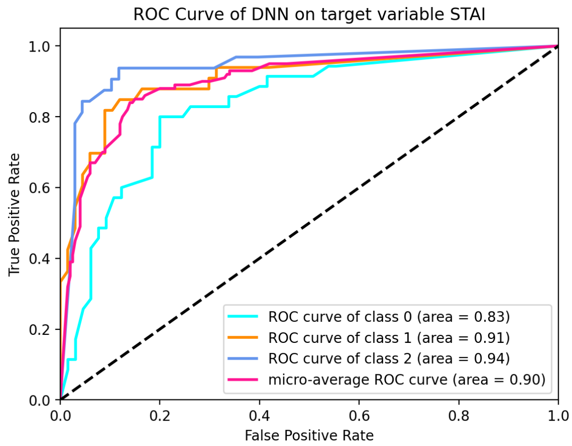
While this study provides insightful data on the mental health, empathy, and burnout levels among medical students in Switzerland, several threats to validity warrant consideration. One of the primary limitations of this study is the relatively small sample size of 886 medical students. This small sample size may not represent the entire population of medical students in Switzerland or elsewhere. The generalizability of the findings may be constrained. Also, the study's cross-sectional design limits the ability to track changes over time, which could be vital in understanding the dynamics of mental health, empathy,



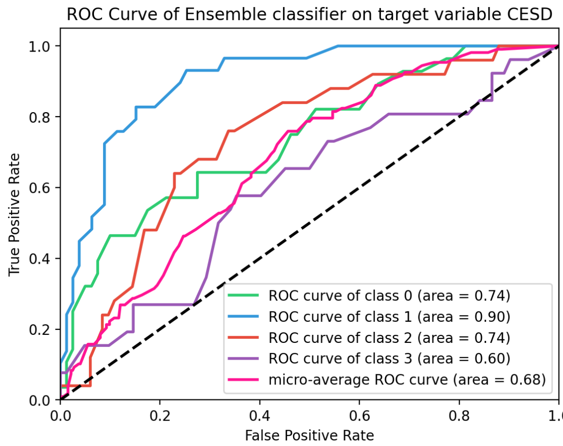
(a)



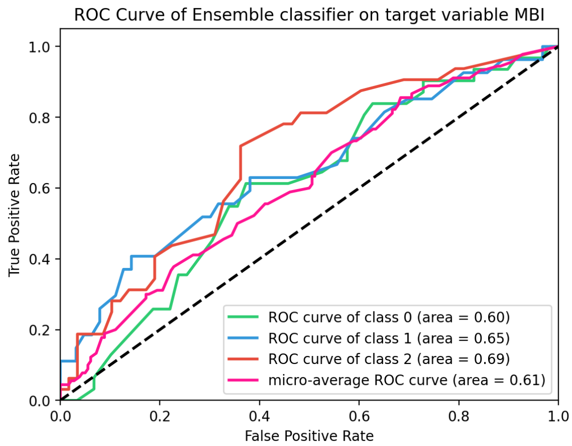
(b)



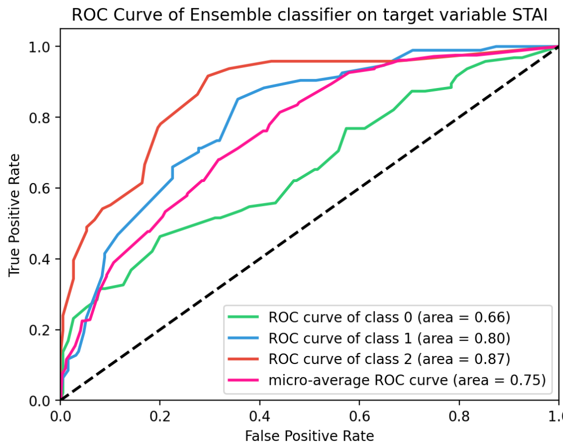
(c)



(d)



(e)



(f)

Figure 36: (a) ROC Curve of DNN on target variable CESD; (b) ROC Curve of DNN on target variable MBI; (c) ROC Curve of DNN on target variable STAI; (d) ROC Curve of Ensemble Classifier on target variable CESD; (e) ROC Curve of Ensemble Classifier on target variable MBI; and (f) ROC Curve of Ensemble Classifier on target variable STAI

and burnout. Furthermore, the dataset exhibits gender imbalance with a predominant

Table 6.4: Result of the ablation study for DNN with different numbers of hidden layers

Label	Number of Hidden Layer	Accuracy (%)	Precision (%)	Recall (%)	MCC (%)	AUC (%)
STAI	1	65.69	65.37	65.34	65.31	65
	2	**81.49**	**79.1**	**80.97**	**79.52**	**81**
	3	77.95	77.78	77.15	77.86	78
	4	78.66	78.22	78.4	78.57	79
CESD	1	55.75	55.21	54.95	54.43	55
	2	**76.65**	**75.98**	**76.27**	**76.04**	**77**
	3	74.7	74.02	73.67	73.2	73
	4	74.96	74.81	73.86	73.76	74
MBI	1	59.85	59.66	59.49	59.4	60
	2	**73.59**	**72.83**	**71.55**	**72.7**	**73**
	3	69.39	69.05	69.15	69.33	69
	4	70.62	70.57	70.45	70.31	70

Table 6.5: Result of the ablation study for Ensemble with different configurations of classifiers

Label	Ensemble Config.	Accuracy (%)	Precision (%)	Recall (%)	MCC (%)	AUC (%)
STAI	RF, NB	72.87	72.85	72.63	72.62	73
	RF, LightGBM	72.97	72.78	72.85	72.34	73
	NB, LightGBM	71.78	71.08	71.23	71.23	71
	RF, LighGBM, NB	**75.8**	**73.51**	**73.97**	**74.89**	**75**
CESD	RF, NB	65.77	65.75	65.23	65.19	66
	RF, LightGBM	64.98	64.92	64.95	64.53	65
	NB, LightGBM	64.74	64.43	63.07	63.56	64
	RF, LighGBM, NB	**67.05**	**66.83**	**66.41**	**65.45**	**68**
MBI	RF, NB	57.46	57.21	57.33	57.04	57
	RF, LightGBM	57.6	57.52	57.73	57.21	57
	NB, LightGBM	59.66	59.39	59.43	59.07	59
	RF, LighGBM, NB	**60.82**	**60.08**	**60.24**	**60.32**	**61**

ratio of female participants (606 females compared to 275 males and 5 non-binary individuals). This disproportionate ratio could introduce bias since the 'sex' feature has a contribution while predicting the outcome, as shown in Fig. 34. Such an imbalance may skew the results and interpretations.

The aforementioned limitations could impact the effectiveness and accuracy of the predictive models developed in this study. The models' ability to generalize and make accurate predictions in different or larger populations of medical students may be restricted due to the sample size and gender distribution limitations.

6.4 Comparison to Prior Works

A comparative analysis is shown in Table 6.6 of the proposed methodology against other studies mentioned in the Background and Related Works section (Section I). Key comparisons include the domain of problem statement which encompasses the mental health issues addressed in the study, and the best performance achieved by our proposed methodology.

This study includes a prediction of three mental health issues, e.g., anxiety, depression, and burnout, while other studies focused on only depression in [5, 27], or only burnout in [59], or a combination of depression, anxiety, and their comorbidity in [13].

Our study achieved the highest accuracy of 81.49%, which is approximately 3.4% better than the result achieved in [59], and approximately 6.5% better than the result achieved in [13]. The DNN method used in this study performed significantly better, achieving a Recall score of 80.97%, which is approximately 27% better in comparison to [27]. Overall, this study showcased significant improvements in performance while additionally incorporating prediction capabilities for anxiety, depression, and burnout.

Table 6.6: Comparative Analysis of Our Proposed Methodology Against Related Prior Work

References	Problem Statement	Algorithms Used	Results
[13]	Automatic identification of depression, anxiety, and comorbidity using textual data of Reddit users	LSTM, AttentionLSTM, Hybrid Lexicon-Based LR, Ensemble of LSTM and Lexicon Based LR	Ensemble method achieved accuracy of 75% and F1 score of 77%
[5]	Depression detection using generated textual data from CLPsych 2015 Shared Task, Reddit, and eRisk	CNN, LSTM, Dense NN	CNN-based classifiers had F1 score around 79%
[27]	Early depression detection using imbalanced social media data	LSTM, Attention-LSTM, Attention-BiLSTM, X-A-BiLSTM	X-A-BiLSTM model achieved highest performance with Precision score of 69%, Recall score of 53%, and F1 score of 60%
[59]	Predict physician burnout using PFI categorical data and EHR audit logs	LR, SVM, RF, gradient boosting tree, MLPNN	MLPNN outperformed other regressors with an accuracy of 78.1%
Our proposed methodology	**Predict anxiety, depression and burnout among medical students**	**DNN & Ensemble Classifier (RF, LightGBM, and NB)**	**DNN outperformed Ensemble Classifier with an accuracy of 81.49%, Precision score of 79.1%, Recall score of 80.97%, and AUC score of 81%**

7 Discussion

7.1 Systematic Literature Review

To develop and assess mobile health applications tailored to the work-related stressors that HCPs encounter, this SLR identified and examined 13 recent studies. The findings imply that mHealth apps present a viable means of conveniently delivering multi-component stress interventions designed for medical professionals. This review includes a comprehensive summary of the mobile applications aimed at regulating mental health for HCPs, highlighting various platforms and key features. The apps' wide range of features did assist in managing and lowering HCPs' stress levels. The main objectives of the reviewed mobile health apps included managing and reducing stress, regulating mental health, and addressing post-traumatic stress symptoms. Certain studies evaluated the results using validated tools like the Professional Quality of Life Scale, EASE Scale, and Maslach Burnout Inventory. The statistical methods mostly used for data analysis across the studies included intention-to-treat analysis, general linear modeling, t-tests, ANOVA/MANOVA, and non-parametric tests such as the Mann-Whitney U test.

Most of the research questions have been thoroughly addressed in this review. It gives a clear landscape of existing mHealth apps, including their features (RQ1, RQ2 for SLR), the psychological interventions that are included (RQ3), the methods for assessment that are employed (RQ4), and the gaps or limitations in the literature (RQ5). Nevertheless, no included study provided a detailed report on security and privacy issues (RQ6). Incorporating such security features that prioritize data privacy and anonymity should be a key consideration for future mHealth apps aimed at helping medical professionals manage stress.

Although this review shows a growing interest in using mHealth apps to integrate proven psychological interventions for HCPs to manage stress, there aren't enough methodologically sound studies with objective outcomes or long-term follow-up data to draw firm conclusions about their effectiveness. To determine the true clinical utility of this approach, larger, more robust trials with objective physiological measures and extensive app usage tracking are required.

7.2 Survey Results and App Development

The stressors and coping mechanisms identified in the survey align with the high demands faced by HCPs, emphasizing the necessity for accessible technological solutions and systemic support. The survey results emphasized the need for mobile apps that provide features like mindfulness, meditation, real-time stress tracking, and tools for assessing workplace stress. These insights directly informed the development of the high-fidelity FreedHCP mHealth app prototype, which incorporates essential features such as chatbot functionality, Wellness Checks, Tasks, Smart Monitoring, and Notifications.

Participants' responses highlighted the importance of features like the Chatbot, Supervisor Dashboard, and Self-Monitoring, which were well-received. Users found the app easy to navigate, visually appealing, and effective for managing stress. A notable 57.7% of respondents expressed their willingness to use the app for real-time stress monitoring.

The prototype also successfully addressed the key research questions. It identified major workplace stressors, coping strategies, and the desired functionalities for a mHealth app aimed at stress management among Bangladeshi HCPs (RQ1 and RQ2). Additionally, the app's evaluation, including user feedback, provided insights into the willingness of HCPs to adopt such a solution (RQ3), further validating the app's relevance and potential for integration into the healthcare setting.

7.3 User-Centered Design Approach

The UCD methodology employed in this study is one of its key strengths, as it involved HCPs throughout the entire process, from the needfinding phase to prototype development and evaluation. This approach ensured that the FreedHCP mHealth solution was tailored to the specific needs and context of its target population, making it highly relevant and practical for the intended users. Moreover, the use of a high-fidelity prototype allowed for comprehensive user testing and feedback, enabling the researchers to gather valuable insights that will inform future refinements and enhancements of the app. This iterative development process ensures that the final product will be well-suited to its users and effective in addressing workplace stress among HCPs.

7.4 Limitations

The limitations to this study are as follows:

- The first limitation is related to the study's design. It was conducted as a cross-sectional study, which can identify correlations but cannot track changes over time. The absence of a longitudinal perspective limits the ability to observe how stressors and coping mechanisms evolve and how effectively the mHealth app supports stress management over an extended period. A longitudinal study would offer more insights into the app's long-term impact on workplace stress.

- The second limitation concerns the choice of measurement scale. The study used SUS to evaluate the app's usability and effectiveness. While SUS is a reliable tool for assessing usability, it captures only one dimension of the app's impact. Other scales and methods could have been employed to measure additional aspects, such as stress reduction, user satisfaction, and the overall efficiency of the app in managing workplace stress. Expanding the evaluation criteria would provide a more comprehensive assessment of the app's effectiveness.

7.5 Additional Features

Additional features could be integrated to further enhance the app's effectiveness. For instance, a social support feature could include peer discussion forums or access to professional guidelines, offering users a space to share experiences and seek advice. This would help reduce feelings of isolation and promote resilience among HCPs.

Moreover, the inclusion of multimedia tools—such as audio guides for relaxation, stress management videos, and calming images—could provide more interactive ways to manage stress. These tools could serve as accessible, on-the-go methods to help users relax and maintain their mental well-being during high-stress periods.

7.6 Impact on Literature

The methodological approach and insights gained from this study provide valuable guidance for researchers focusing on mHealth solutions for stress management within the healthcare sector. The findings underscore the importance of a user-centered design, emphasizing that apps should be tailored to specific cultural and professional contexts. This adaptability can enhance the relevance and effectiveness of similar applications in different settings.

Additionally, the user evaluation process and the assessment of acceptance factors offer a framework for researchers to design robust user testing protocols. This can help in identifying user needs and preferences early in the development process, ultimately leading to the creation of more user-friendly and impactful mHealth interventions. By applying these methodologies, future studies can enhance the effectiveness of stress management tools for HCPs globally.

7.7 How Chapter 6 can contribute to the main idea

The DL based method developed in chapter 6 for screening anxiety, depression, and burnout hold substantial value in the broader context of our FreedHCP app. By accurately identifying mental health challenges such as burnout, anxiety, and depression, this DL-based model offer several foundational advantages to the proposed stress management mHealth app and enhances its capacity for automated stress detection:

- By incorporating the DL-based detection method, it allows the FreedHCP app to provide a refined understanding of users' mental health states. Since burnout, anxiety, and depression are significant indicators of chronic stress, the ability to screen for these conditions can enhance the accuracy and precision of stress classification. When combined with data from wearable sensors, such as heart rate variable, blood pressure, and oxygen levels, this model-based approach will be able to detect complex patterns of stress responses that might otherwise be challenging to capture solely through physiological data.
- The DL-based method developed in chapter 6 can contribute to the personalization of stress management interventions within the FreedHCP app. By identifying specific mental health conditions, the app will be able to tailor coping strategies and recommendations more effectively. For instance, users with a high likelihood of burnout may benefit from different support options than those with predominant symptoms of anxiety or depression.
- By utilizing the DL-based method that would continuously learn and adapt based on new data, the FreedHCP app can improve its stress detection accuracy over time. This adaptability is crucial in a healthcare setting, as individual stress responses may evolve due to changing workplace demands and personal factors. Continuous learning ensures that the app remains relevant and responsive to HCPs needs, reinforcing its effectiveness as a tool for stress management.

8 Conclusion and Future Works

8.1 Conclusion

The purpose of this study was to develop an evidence-based mobile app for stress management tailored to HCPs in Bangladesh. The primary aim was to identify the main stressors they face and their coping mechanisms, leading to the creation of a prototype app designed to optimize mHealth solutions for this population. By analyzing existing literature on mHealth interventions addressing workplace stress, key features such as self-monitoring and social support were identified as essential components.

The survey revealed that heavy workloads and work-life imbalance are significant stressors for HCPs, while common coping mechanisms include seeking social support, taking breaks, and effective time management. Furthermore, participants expressed a need for enhanced app functionalities, specifically highlighting the importance of features like 'Meditation and Relaxation Exercises' and 'Personalized Stress Management'.

This research makes a valuable contribution toward developing a robust mHealth stress management solution, empowering HCPs not only in Bangladesh but potentially in other contexts as well. The findings emphasize the importance of a UCD approach, providing insights that inform both the design and implementation of the app to meet the specific needs of HCPs effectively.

8.2 Future Plan

Demonstration of the prototype evaluation was beneficial for the users, but usability improvements are still needed. There is room for future work that includes

- Taking surveys from a larger sample that incorporates psychological indicators and other biological data rather than solely relying on self-reported data that only have a participant's perception, attitudes, and feelings.
- Developing FreedHCP as a cross-platform mHealth app that will operate on various devices and operating systems. This will make the mHealth app more accessible to a broader range of users and benefit a diverse group of HCPs.
- Generate a Stress Dataset that would classify the stress levels of individual participants along with their corresponding health vitals including heart rate variable, blood pressure, and oxygen, all while they perform various experimentally designed mentally stressful tasks.
- Conducting a longitudinal study, which will allow the researchers to track and analyze the long-term effectiveness of the mHealth app in managing stress.

- Integrating the mHealth app with smartwatches to enhance the app's functionality by enabling real-time stress monitoring and data collection. By leveraging the capabilities of smartwatches to track physiological data, FreedHCP will offer more personalized and immediate support to HCPs.
- Incorporating the proposed DL-based automated method for stress detection into the backend of a fully functional app for stress management of HCPs

A Appendix

A.1 Appendix A: Abbreviations

1. **HCP:** Healthcare Professionals
2. **LMIC:** Lower- and Middle-Income Countries
3. **mHealth:** Mobile Health
4. **DL:** Deep Learning
5. **SUS:** System Usability Scale
6. **ML:** Machine Learning
7. **RF:** Random Forest
8. **NB:** Naive Bayes
9. **LightGBM:** Light Gradient Boosting Machine
10. **DNN:** Deep Neural Network
11. **AI:** Artificial Intelligence
12. **HCI:** Human-Computer Interaction
13. **UCD:** User-Centered Design
14. **AR:** Augmented Reality
15. **VR:** Virtual Reality
16. **EHR:** Electronic Health Record
17. **SMS:** Short Message Service
18. **HRV:** Heart Rate Variability
19. **AUC:** Area Under the Curve
20. **IRB:** Institutional Review Board
21. **RQ:** Research Question
22. **SLR:** Systematic Literature Review
23. **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses

24. **MBI:** Maslach's Burnout Inventory
25. **PQL:** Professional Quality of Life
26. **CBT:** Cognitive Behavioral Therapy
27. **PSS-4:** 4-item Perceived Stress Scale
28. **SPIRIT:** Standard Protocol Items: Recommendations for Interventional Trials
29. **REBEC:** Brazilian Clinical Trials Registry
30. **PHQ-8:** 8-item Patient Health Questionnaire
31. **GAD-2:** 2-item Generalized Anxiety Disorder Scale
32. **PTSD:** Post-Traumatic Stress Disorder
33. **PCL-5:** PTSD Checklist for DSM-5
34. **DSM-5:** Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
35. **CD-RISC2:** 2-item Connor-Davidson Resilience Scale
36. **WHO-5:** 5-item World Health Organization Well-Being Index
37. **AUDIT-C:** Alcohol Use Disorders Identification Test-Concise
38. **PDF:** Portable Document Format
39. **SD:** Standard Deviation
40. **CESD:** Center for Epidemiologic Studies Depression
41. **STAI:** State and Trait Anxiety Inventory
42. **SMHD:** Self-Reported Mental Health Diagnoses
43. **LSTM:** Long Short-Term Memory
44. **CNN:** Convolutional Neural Network
45. **LR:** Logistic Regression
46. **PFI:** Professional Fulfillment Index
47. **SVM:** Support Vector Machine
48. **MLPNN:** Multi-Layer Perceptron Neural Network
49. **RSDD:** Reddit Self-Reported Depression Diagnoses
50. **XGBoost:** Extreme Gradient Boosting
51. **QCAE:** Questionnaire of Cognitive and Affective Empathy
52. **AMSP:** Ability to Modify Self-Presentation
53. **ReLU:** Rectified Linear Unit

54. **DT:** Decision Tree

55. **IG:** Information Gain

56. **MCC:** Matthews Correlation Coefficient

57. **ROC-AUC:** Receiver Operating Characteristic Area Under the Curve

58. **TP:** True Positive

59. **TN:** True Negative

60. **FP:** False Positive

61. **FN:** False Negative

A.2 Appendix B: List of Key Publications from this Work

1. M. Islam, S. Rashid, L. Rafid, T. Badrul, A. Islam and B. M. Chaudhry, ”Design and Evaluation of a Smartwatch-Based Physiological Signal-Driven Workplace Stress Management mHealth Tool for Bangladeshi Healthcare Professionals,” Presented at the 2024 Advances in Science and Engineering Technology International Conferences (ASET) International Multi-Conferences (June 2024), IEEE.

2. S. Rashid, T. Badrul, L. Rafid, J. H. Setu, N. Halder and A. Islam, ”Ensemble and Deep Learning Approaches for Automated Screening of Anxiety, Depression, and Burnout in Medical Student Populations,” Presented at the 2024 Advances in Science and Engineering Technology International Conferences (ASET) International Multi-Conferences (June 2024), IEEE.

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