MINDSCULPTOR: AN OBSESSIVE-COMPULSIVE DISORDER (OCD) EXPOSURE AND RESPONSE PREVENTION (ERP) THERAPY TOOL

24-25J-046

Project Proposal Report

Vithanage C.S.

B.Sc. (Hons) Degree in Information Technology Specialized in Software Engineering

Department of Computer Science and Software Engineering

Sri Lanka Institute of Information Technology, Sri Lanka

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DECLARATION OF THE CANDIDATE AND SUPERVISOR.

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ABSTRACT

Obsessive-Compulsive Disorder (OCD) is a complex mental health condition that necessitates accurate and thorough assessment for effective treatment. This research proposes an advanced system that combines dynamic questionnaires, voice analysis, and voice pitch fluctuation analysis to evaluate the presence, severity, and subtypes of OCD in patients.

The system begins with a dynamic questionnaire, customized to adapt in real-time to the patient's responses, ensuring a personalized and comprehensive assessment. To further enhance the diagnostic process, patient voice recordings are analyzed to identify key OCD-related expressions and behaviors. Additionally, fluctuations in voice pitch are examined to gain insights into the patient’s emotional state and behavioral patterns.

By integrating the findings from the dynamic questionnaire, keyword detection in voice recordings, and pitch analysis, the proposed system provides a holistic and robust diagnosis of OCD. This approach not only aims to improve diagnostic accuracy but also contributes to a deeper understanding of the patient's condition, making it a valuable tool for clinicians and mental health professionals.

Keywords: Obsessive-Compulsive Disorder (OCD), Dynamic Questionnaire, Voice Analysis, Pitch Fluctuation Analysis, Mental Health Assessment.

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LIST OF ABBREVIATIONS

Abbreviations	Description
OCD	Obsessive-Compulsive Disorder
Y-BOCS	Yale-Brown Obsessive-Compulsive Scale
NLP	Natural Language Processing
ASR	Automatic Speech Recognition
TF-IDF	Term Frequency-Inverse Document Frequency
SVM	Support Vector Machine
AI	Artificial Intelligence
ML	Machine Learning
ERP	Exposure and Response Prevention
CBT	Cognitive-Behavioral Therapy
OCI-R	Obsessive-Compulsive Inventory-Revised
CNN	Convolutional Neural Networks
IVA	Interactive Voice Assistants
DB	Database
UI	User Interface
CI/CD	Continuous Integration/Continuous Deployment

1. INTRODUCTION

1.1 BACKGROUND

Obsessive-Compulsive Disorder (OCD) is a prevalent mental health condition characterized by persistent, unwanted thoughts (obsessions) and repetitive behaviors (compulsions). Accurately diagnosing OCD and assessing its severity and subtypes are crucial for effective treatment and management. Traditional methods of diagnosis often rely on clinical interviews and self-report questionnaires, which, while effective, have certain limitations. Advances in technology and data analysis have opened new avenues for more sophisticated diagnostic tools, integrating voice analysis and dynamic questionnaires.

Historically, the diagnosis of OCD has been heavily reliant on tools like the Yale-Brown Obsessive-Compulsive Scale (Y-BOCS) and clinical assessments by mental health professionals. While these methods are thorough, they can be time-consuming and dependent on the clinician's experience. Recent research has explored automated systems that can supplement these traditional methods, offering real-time, scalable, and objective assessments of OCD symptoms. These systems often incorporate advanced machine learning algorithms, natural language processing (NLP), and voice analysis to detect nuanced indicators of OCD.

One of the core innovations in modern mental health diagnostics is the use of dynamic questionnaires. Unlike static questionnaires, which present a fixed set of questions, dynamic questionnaires adapt based on user responses, allowing for a more personalized and accurate assessment. This approach is particularly useful in diagnosing OCD, where symptom presentation can vary widely among individuals. By tailoring questions to the individual's responses, dynamic questionnaires can more effectively identify specific subtypes of OCD and assess the severity of symptoms.

Dynamic questionnaires also address some limitations of traditional methods, such as patient fatigue and response bias. By presenting questions that are more relevant to the individual's specific symptoms, these tools can maintain user engagement and provide more accurate data for diagnosis. Additionally, integrating machine learning models with these questionnaires allows for the continuous improvement of the diagnostic process, as the system can learn from each interaction to better predict and assess OCD symptoms in the future.

Voice analysis is an emerging field in mental health diagnostics, offering a non-invasive, objective method to assess psychological conditions. For OCD diagnosis, voice analysis can provide valuable insights into the emotional and cognitive states of individuals. Specific patterns in voice pitch, tone, and speech rate can indicate levels of distress, anxiety, and compulsion, which are core features of OCD.

The application of Automatic Speech Recognition (ASR) APIs, combined with algorithms like TF-IDF (Term Frequency-Inverse Document Frequency) and Support Vector Machines (SVM), enables the detection of keywords and phrases associated with OCD. For instance, certain obsessive thoughts may be frequently verbalized, and compulsive behaviors might be reflected in the repetition of specific words or phrases. By analyzing these patterns, voice analysis tools can help identify the presence of OCD and provide a preliminary assessment of its severity.

Furthermore, voice pitch fluctuation analysis can offer insights into the emotional state of the individual, which is often linked to the severity of OCD symptoms. For example, significant pitch variations might indicate heightened anxiety or stress, both of which are commonly associated with OCD. By integrating voice analysis with dynamic questionnaires, the diagnostic process becomes more comprehensive, capturing both the cognitive and emotional dimensions of OCD.

While these technological advancements hold significant promise, they also present challenges. The accuracy of voice analysis can be influenced by various factors, such as background noise, accents, and speech disorders. Additionally, the effectiveness of dynamic questionnaires depends on the quality of the algorithms used to adapt the questions and the initial data fed into the system. Therefore, continuous refinement of these tools is necessary to ensure they provide reliable and valid assessments.

In summary, the integration of dynamic questionnaires and voice analysis into the diagnostic process represents a significant advancement in the field of mental health, particularly for conditions like OCD. These tools offer the potential for more personalized, efficient, and accurate assessments, which can improve treatment outcomes for patients. As these technologies continue to evolve, they hold the promise of transforming how we approach mental health diagnostics, making them more accessible and effective for a broader population.

1.2 LITERATURE REVIEW

Obsessive-Compulsive Disorder (OCD) is a chronic mental health condition characterized by recurring thoughts (obsessions) and repetitive behaviors (compulsions). The complexity and severity of OCD has prompted significant research into various therapeutic approaches and technological interventions aimed at managing the condition. In recent years, digital health technologies, including mobile applications, have emerged as promising tools for enhancing traditional therapeutic practices.

Mobile Application Interventions

The integration of mobile applications into OCD treatment has gained traction, as highlighted by Pascual-Vera et al. (2018). Their study focused on a mobile app-based intervention designed to assist in the prevention of OCD relapse. The intervention incorporated cognitive-behavioral techniques, particularly Exposure and Response Prevention (ERP), into a mobile platform. The case report demonstrated the app's effectiveness in providing continuous support to patients, thereby reducing the risk of relapse. The study also emphasized the app's potential for widespread adoption, given its accessibility and ease of use [1].

Building on this, Gershkovich et al. (2021) explored the feasibility and acceptability of integrating ERP with a mobile app specifically tailored for OCD treatment. Their research found that mobile apps could significantly enhance user engagement and treatment adherence, making therapeutic interventions more effective. The preliminary effects of this integration showed promising reductions in OCD symptom severity, indicating that mobile apps could serve as a valuable adjunct to traditional therapy [2].

In a related study, Hull and Mahan (2017) investigated the use of asynchronous mobile-enabled SMS text psychotherapy for OCD. This approach provided an alternative for patients who may not have access to in-person therapy. The study revealed that text-based interventions could deliver timely and effective support, helping patients manage their symptoms remotely. The research highlighted the potential of SMS-based therapy as a cost-effective and accessible solution for OCD treatment, particularly in underserved populations [3].

Web-Based and Digital Platforms

In addition to mobile apps, web-based platforms have also shown promise in OCD management. McIngvale et al. (2012) examined the effectiveness of an interactive self-help website for individuals with OCD. The website offered a range of resources, including self-help materials, interactive tools, and community support. The study found that users who engaged with the website experienced reductions in OCD symptoms and an overall improvement in mental health. The research underscored the potential of web-based platforms to provide scalable and affordable mental health support [4].

Implications for Future Research and Practice

The integration of technology into OCD treatment represents a significant shift in the approach to managing the disorder. The studies reviewed highlight the potential of mobile apps, web-based platforms, AI, and VR in enhancing traditional therapeutic practices. These technologies offer accessible, scalable, and cost-effective solutions that can complement existing treatment modalities, making OCD management more effective and personalized.

However, the adoption of these technologies also presents challenges, including issues related to data privacy, user engagement, and the need for further validation through large-scale clinical trials. Future research should focus on addressing these challenges and exploring the long-term efficacy of digital interventions in OCD treatment.

1.3 RESEARCH GAP

Research A [1] - GGOC: OCD Relief employs static questionnaires for diagnosing OCD, which may not capture the full complexity of individual patient experiences. The system relies on fixed questions, potentially missing critical nuances in symptom severity and sub-types. In contrast, our proposed system utilizes dynamic questionnaires that adapt based on real-time user responses. This personalization enhances diagnostic accuracy by tailoring questions to each patient's unique needs, addressing a key limitation in GGOC: OCD Relief's approach.

Research B [2] - nOCD primarily uses text input for managing OCD symptoms, which may not fully convey the depth of a patient's experiences. Our system introduces voice input for describing OCD episodes, offering a more nuanced understanding of the patient's condition. By capturing verbal descriptions, our system provides a richer, more detailed analysis compared to nOCD, ensuring that subtleties in the patient's experience are better addressed.

Research C [3] - TalkSpace focuses on text-based therapy and lacks the capability to analyze voice data, missing important verbal cues that could indicate symptom severity or specific OCD subtypes. Our system integrates keyword detection in voice recordings, capturing critical verbal indicators that TalkSpace overlooks. This feature allows for a more comprehensive analysis of the patient's condition, making our system a more robust diagnostic tool compared to TalkSpace.

Research D [4] - OCD Challenge is a self-help tool that does not incorporate voice analysis, potentially missing key emotional cues reflected in a person's voice. Our system introduces voice pitch analysis to assess emotional states underlying OCD symptoms, offering insights that OCD Challenge does not provide. This focus on emotional analysis through voice data enhances the understanding of the patient’s condition and offers a more holistic diagnostic approach.

1.3.1 RESEARCH GAP TABLE

Feature	Proposed System	Research A	Research B	Research C	Research D
Dynamic Questionnaires	✓	✗	✓	✗	✓
Explain OCD Episodes as Voice	✓	✗	✗	✗	✗
Keyword Detection in Voice	✓	✗	✗	✗	✗
Voice Pitch Fluctuation Analysis	✓	✗	✗	✗	✗
Accurate Diagnosis	✓	✗	✗	✗	✗
Data Privacy	✓	✓	✓	✓	✓

Table 1: Research Gap Table

1.4 RESEARCH PROBLEM

The diagnosis and treatment of obsessive-compulsive disorder (OCD) are fraught with challenges that current technological interventions struggle to address effectively. Despite the availability of various mobile applications like GGOC: OCD Relief, nOCD, and TalkSpace, there remains a significant gap in accurately diagnosing and treating OCD due to the limitations of these platforms. These applications primarily rely on static questionnaires and text-based inputs, which do not capture the complexities of OCD symptoms that often manifest in fluctuating thought patterns and anxiety levels.

Moreover, the lack of dynamic, voice-enabled interaction limits the ability of these applications to adapt to real-time user responses, which is crucial for an accurate diagnosis and effective treatment. Additionally, these systems do not leverage the potential of voice pitch fluctuation analysis or keyword detection within voice inputs to assess the severity of OCD symptoms more precisely. This gap in technology is exacerbated by concerns over data privacy, especially when dealing with sensitive mental health information, which is not adequately addressed in current systems.

Given these limitations, the primary research problems identified are:

1. How can we develop a voice-enabled chatbot system capable of capturing the dynamic nature of OCD symptoms to enhance the accuracy of diagnosis and treatment?

2. What methods can be employed to analyze voice pitch fluctuations and keyword detection in real-time to assess the severity and subtypes of OCD more effectively?

3. How can data privacy be ensured in a system that relies heavily on voice data for diagnosing and treating OCD, while still providing accurate and personalized care?

4. How can the integration of dynamic questionnaires and voice-based interactions improve patient engagement and the overall efficacy of OCD treatment?

These research problems aim to address the current shortcomings in OCD diagnosis and treatment by exploring innovative technological solutions that enhance the accuracy and personalization of care, while also ensuring the privacy and security of patient data.

2. OBJECTIVES

2.1 MAIN OBJECTIVE

The primary objective of this component is to develop a comprehensive system for identifying the presence, severity, and subtypes of Obsessive-Compulsive Disorder (OCD) in patients. This system is designed to enhance traditional diagnostic methods by integrating innovative technologies, including dynamic questionnaires, voice analysis, and machine learning algorithms. The goal is to provide a more accurate, efficient, and personalized diagnostic tool that can assist clinicians in making informed decisions about treatment strategies.

The dynamic questionnaire, built upon established scales such as the Yale-Brown Obsessive Compulsive Scale (Y-BOCS) and the Obsessive-Compulsive Inventory-Revised (OCI-R), forms the foundation of the diagnostic process. This questionnaire is designed to adapt to the user's responses in real-time, allowing for a more nuanced understanding of the patient's symptoms. The system's voice analysis component adds another layer of insight by capturing and analyzing voice recordings, using techniques like keyword detection and pitch fluctuation analysis to assess the patient's emotional state and behavioral patterns. By combining these data points, the system aims to provide a holistic and reliable diagnosis of OCD, categorizing it into specific subtypes and determining its severity.

1.2 SPECIFIC OBJECTIVES

- **Dynamic Questionnaire Implementation:**

  Develop a dynamic questionnaire that consists of 20 questions, derived from the Y-BOCS, OCI-R, and custom questions tailored to the application. The questionnaire is designed to adjust the sequence of questions based on the patient's previous responses, ensuring a personalized and thorough assessment of OCD symptoms. The ultimate goal is to generate accurate results indicating the presence, severity, and subtype of OCD.

- **Integration of Keyword Detection:**

  Incorporate keyword detection from voice recordings into the assessment process. This involves using an Automatic Speech Recognition (ASR) API, such as Google Cloud Speech-to-Text, to transcribe voice recordings into text. A Support Vector Machine (SVM) model is then trained to identify specific keywords within the text that correlate with OCD symptoms. This process enhances the diagnostic accuracy by providing additional context to the patient's verbal expressions of their experiences.

- **Voice Pitch Fluctuation Analysis:**

  Utilize advanced audio analysis techniques, specifically the Librosa library, to analyze pitch fluctuations in the patient's voice recordings. This analysis aims to derive insights into the patient's emotional state and behavioral tendencies when discussing their OCD experiences. The findings from this analysis are intended to supplement the questionnaire results, offering a more comprehensive evaluation of the patient's condition.

- **Combining Results Using Ensemble Learning:**

  Develop an algorithm that integrates the results from the dynamic questionnaire, keyword detection, and pitch analysis. By applying ensemble learning techniques, the system will combine these various data sources to produce a final, robust diagnosis. The objective is to ensure that the diagnostic process is both thorough and reliable, minimizing the risk of misdiagnosis and enabling more effective treatment planning.

  These specific objectives collectively contribute to the development of a cutting-edge diagnostic tool that not only identifies OCD but also provides a detailed analysis of its severity and subtype. This tool is intended to support clinicians in delivering more targeted and effective treatments, ultimately improving patient outcomes.

3. METHODOLOGY

3.1 RESEARCH AREA

This research focuses on advancing the diagnosis and treatment of Obsessive-Compulsive Disorder (OCD) by leveraging cutting-edge technologies such as biometric data analysis, artificial intelligence (AI), machine learning (ML), and natural language processing (NLP). The research is grounded in the field of digital mental health, where the integration of these technologies can significantly improve the accuracy and efficiency of OCD assessments and interventions.

1. **Digital Mental Health and Diagnostic Tools**: The primary area of research is the development of a comprehensive digital therapy platform that incorporates dynamic questionnaires, voice analysis, and pitch fluctuation analysis to diagnose OCD. This involves exploring the use of established psychological scales like the Yale-Brown Obsessive Compulsive Scale (Y-BOCS) and the Obsessive-Compulsive Inventory-Revised (OCI-R), alongside custom question sets, to create a dynamic, responsive diagnostic tool. The focus is on how AI can optimize the sequence and relevance of questions based on real-time patient responses, thereby improving the diagnostic accuracy for OCD presence, severity, and subtypes.

2. **Biometric Data and Exposure Therapy:** Another key research area is the enhancement of Exposure and Response Prevention (ERP) therapy using biometric data. The study investigates how AI and ML can be used to simulate OCD-triggering scenarios, assess patient reactions through facial expression analysis, and predict treatment outcomes. The research extends to the application of computer vision and deep learning models, like convolutional neural networks (CNNs), to analyze patient responses in real-time and adapt therapeutic interventions accordingly.

3. **Natural Language Processing in Therapy:** The research also delves into the use of NLP and AI-supported Interactive Voice Assistants (IVAs) for delivering personalized therapy sessions. This involves studying the effectiveness of voice pitch analysis and keyword detection in identifying OCD subtypes and tailoring therapeutic dialogues. The application of signal processing techniques for emotion detection in patient speech is a critical aspect of this research, contributing to more personalized and responsive therapy sessions.

4. **AI-Enhanced Telemedicine:** Finally, the research explores the integration of AI in video conferencing tools for ERP therapy. This involves examining how real-time biometric data, such as facial expressions and voice modulations, can be captured and analyzed to enhance the interaction between therapists and patients. The goal is to provide a robust platform that not only facilitates remote therapy but also enhances the monitoring and treatment of OCD through advanced AI analytics.

This research is positioned at the intersection of psychology, digital health, and AI, aiming to create innovative solutions that enhance the diagnosis and treatment of OCD, ultimately contributing to the broader field of mental health technology.

3.2 OVERALL SYSTEM DESCRIPTION AND DIAGRAM

The proposed system is designed to enhance and streamline the process of diagnosing and treating Obsessive-Compulsive Disorder (OCD) through a comprehensive, AI-enhanced platform that integrates video conferencing and virtual ERP (Exposure and Response Prevention) therapy. This system leverages AI technology to enable remote intervention, ensuring that patients receive timely and effective treatment regardless of their location.

System Workflow:

1. **User Interaction:** The process begins with the patient using a mobile application to report symptoms or concerns related to OCD. The app provides an interface for initial data input, allowing the patient to describe symptoms or upload relevant images and videos.

2. **Diagnosis of OCD:** The input data is analyzed to identify the presence of OCD. The system determines the severity, subtype (e.g., contamination, symmetry), and presence of OCD through advanced AI algorithms. This step is crucial for tailoring the subsequent therapeutic interventions.

3. **Data Storage:** The diagnosis results, including severity, subtype, and any related images or videos, are securely stored in a centralized database (DB). This allows healthcare providers to access and review patient information efficiently.

4. **AI-Enhanced Video Conferencing:** If the severity of OCD is high, the system facilitates a video conferencing session between the patient and a healthcare provider (doctor). This session is enhanced by AI to ensure that the therapist can effectively engage with the patient and make informed decisions during the session. The video conferencing module is integrated into both a web application and a mobile application, allowing flexibility in how the session is conducted.

5. **Virtual ERP Therapy (VERP):** For patients with mild to moderate severity, where the OCD subtype is related to contamination or symmetry, the system automatically initiates virtual ERP therapy. This therapy involves displaying relevant videos and images via the mobile or web app to help the patient gradually confront and manage their OCD symptoms.

6. **AI Voice Assistant:** For other OCD subtypes, such as checking and washing, the system deploys an AI voice assistant. This assistant guides the patient through tailored therapeutic exercises, helping them build resilience and manage their symptoms effectively. The assistant also uses conversational AI to maintain engagement and track the patient’s progress.

7. **Session Analysis and Continuous Monitoring:** Post-session, the data from both the video conference and ERP therapy sessions are analyzed and stored in the database.

This data is used for further analysis to track the patient's progress and adjust treatment plans as necessary.

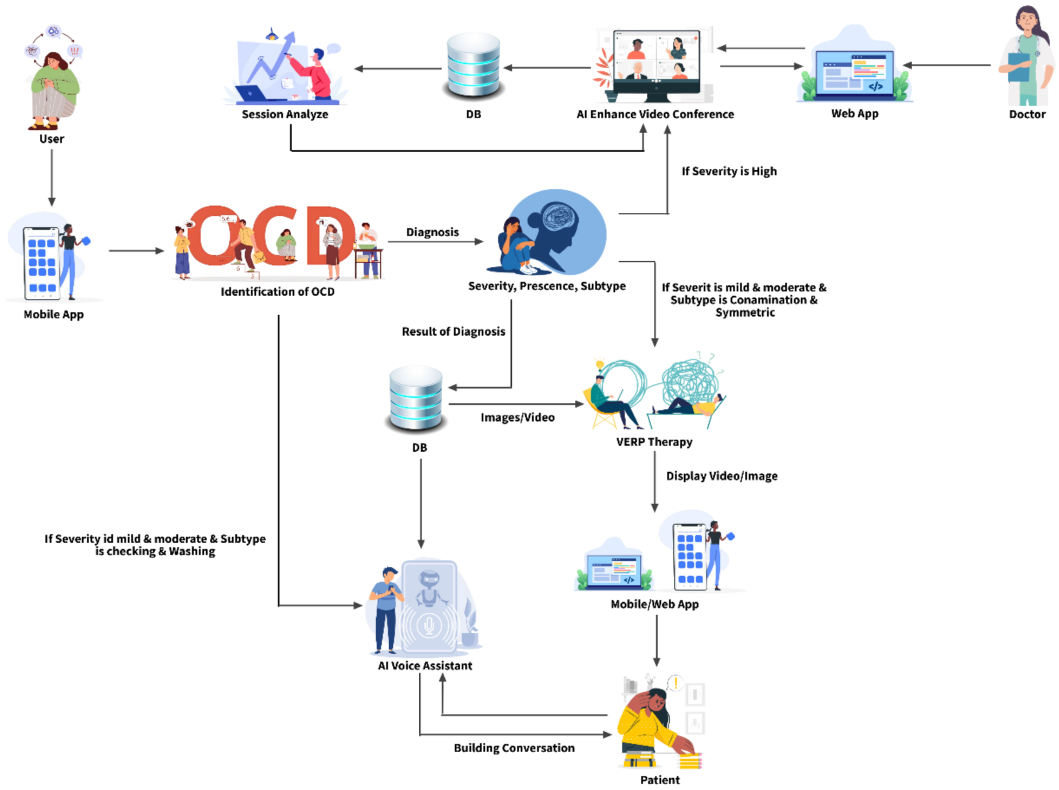


Figure 1: Overall System Diagram

The diagram illustrates the flow of information and the interaction between various components of the system. It highlights the different pathways depending on the severity and subtype of OCD, ensuring that each patient receives a tailored and effective intervention. The integration of AI at various stages ensures that the system is responsive, adaptive, and capable of providing high-quality remote care.

This system represents a significant advancement in the remote treatment of OCD, utilizing AI-driven technologies to enhance accessibility, personalize care, and improve outcomes for patients.

3.3 INDIVIDUAL COMPONENT DESCRIPTION AND DIAGRAM

This component aims to enhance the traditional approaches to OCD diagnosis by integrating a dynamic questionnaire, voice analysis, and machine learning techniques to offer a more personalized and accurate evaluation of patients.

At the core of this component is the dynamic questionnaire, designed to assess the presence and severity of OCD. The questionnaire is structured around well-established scales, including the Yale-Brown Obsessive Compulsive Scale (Y-BOCS) and the Obsessive-Compulsive Inventory-Revised (OCI-R). These scales are widely recognized in the clinical community for their reliability and validity in diagnosing OCD. The questionnaire also includes custom questions tailored to the specific needs of the application, ensuring that the assessment is comprehensive and relevant.

The dynamic nature of the questionnaire allows it to adapt to the user's responses in real-time. This means that the sequence of questions can be adjusted based on the answers provided by the patient, enabling a more focused and efficient assessment process. For instance, if a patient indicates a high level of distress related to a specific symptom, the questionnaire can delve deeper into that area, asking more detailed questions to better understand the severity and impact of that symptom. This approach not only saves time but also ensures that the most relevant information is gathered, leading to a more accurate diagnosis.

The responses collected through the questionnaire are then analyzed to generate results that indicate the presence of OCD, the severity of the disorder, and the specific subtype of OCD that the patient may be experiencing. The subtypes could include contamination, harm, symmetry, or other common OCD themes. The results from the questionnaire provide a foundation for the subsequent steps in the diagnostic process, which involve voice analysis and the integration of data to refine the diagnosis.

Voice analysis is a novel feature of this component that adds a new dimension to the assessment of OCD. By capturing and analyzing voice recordings of patients describing their OCD experiences, this feature aims to provide additional insights into the patient's condition that may not be captured through the questionnaire alone. The voice recordings are processed using Automatic Speech Recognition (ASR) APIs, such as Google Cloud Speech-to-Text or IBM Watson. These APIs convert the spoken words into text, which can then be analyzed for specific keywords and patterns associated with OCD.

The keyword detection process is carried out using a Support Vector Machine (SVM) model, a powerful machine learning algorithm that can classify data into different categories. In this context, the SVM model is trained to identify keywords that are indicative of OCD symptoms. For example, if a patient frequently mentions words related to contamination or harm, the system can use this information to corroborate the results from the questionnaire and provide a more nuanced diagnosis.

In addition to keyword detection, the voice analysis component also includes an assessment of voice pitch fluctuations. By analyzing the pitch of the patient's voice, the system can gain insights into the patient's emotional state and behavioral tendencies. For instance, a significant fluctuation in pitch may indicate heightened anxiety or distress, which could be linked to the severity of OCD symptoms. The pitch analysis is performed using the Librosa library, a powerful tool for audio and music analysis. The results from the pitch analysis are used to enhance the overall diagnostic process, providing a more holistic view of the patient's condition.

The final step in this component involves combining the results from the dynamic questionnaire, keyword detection, and pitch analysis to generate a comprehensive diagnosis. This is achieved through the use of ensemble learning techniques, which are designed to combine multiple models to produce a more accurate and reliable prediction. In this case, the different data points collected from the questionnaire, voice analysis, and pitch analysis are integrated into a single algorithm that generates the final diagnosis.

The ensemble learning approach ensures that the strengths of each individual method are leveraged, while the weaknesses are minimized. For example, while the questionnaire provides detailed information about the patient's symptoms, it may not capture the emotional nuances that can be detected through voice analysis. Similarly, while voice analysis can provide insights into the patient's emotional state, it may not be as effective in identifying the specific subtype of OCD. By combining these different approaches, the system can provide a more comprehensive and accurate diagnosis, reducing the risk of misdiagnosis and enabling more effective treatment planning.

By integrating traditional diagnostic methods with cutting-edge technologies such as dynamic questionnaires, voice analysis, and machine learning, this component aims to provide a more accurate, efficient, and personalized assessment of OCD. The development of this system has the potential to revolutionize the way OCD is diagnosed, offering clinicians a powerful tool to assist in the treatment of this complex disorder. Through the combination of various data sources and the use of ensemble learning techniques, the system is designed to provide a robust and reliable diagnosis, ultimately improving patient outcomes and enhancing the overall quality of care.

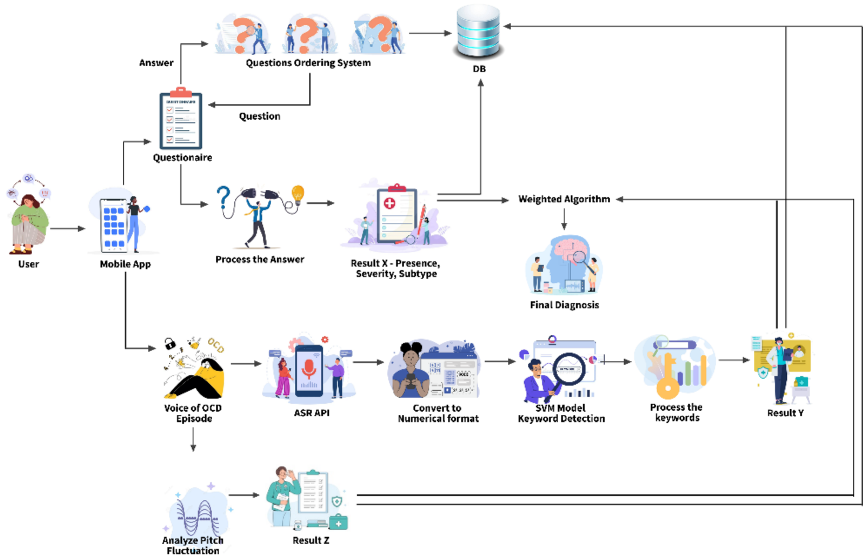


Figure 2: Individual Component Diagram

3.4 SOFTWARE ARCHITECTURE

The software architecture for identifying the presence, severity, and subtypes of OCD in patients is designed to integrate advanced machine learning models, voice analysis, and dynamic questionnaires into a cohesive system. This architecture is divided into several layers, each responsible for specific functionalities, ensuring a scalable, secure, and efficient solution.

1. Presentation Layer

User Interface (UI): This layer is responsible for interacting with patients and clinicians. It includes a web-based and mobile-responsive application developed using frameworks like

React.js for web and React Native for mobile. The UI provides a dynamic questionnaire interface, voice recording functionality, and displays results.

Dynamic Questionnaire Module: Embedded within the UI, this module presents a set of 20 questions derived from established OCD scales such as Y-BOCS and OCI-R. The order of questions is dynamically adjusted based on the user's responses, creating a personalized diagnostic experience.

2. Application Layer

Questionnaire Processing Engine: This engine is responsible for handling the logic behind the dynamic questionnaire. It manages the flow of questions, processes user responses in real-time, and interacts with the back-end server to update the severity and subtype analysis based on responses.

Voice Analysis Module: This module captures and processes voice recordings from patients. It utilizes APIs like Google Cloud Speech-to-Text for transcribing speech to text and incorporates a Support Vector Machine (SVM) model for keyword detection within the transcribed text.

Pitch Analysis Module: The pitch analysis module leverages libraries like Librosa to analyze fluctuations in the patient’s voice pitch, providing additional insights into the emotional state and severity of the OCD symptoms.

Results Integration Engine: This engine integrates data from the questionnaire, voice analysis, and pitch analysis. It uses ensemble learning techniques to combine these inputs and generate a comprehensive assessment of the presence, severity, and subtypes of OCD.

3. Data Layer

Patient Data Repository: This database stores all patient-related information, including questionnaire responses, voice recordings, and analysis results. It is designed with privacy and security in mind, ensuring compliance with healthcare regulations like HIPAA or GDPR.

Model Training and Storage: This sub-layer stores pre-trained machine learning models, such as the SVM for keyword detection and models for voice pitch analysis. It also handles updates to these models based on new data, ensuring continuous improvement in diagnostic accuracy.

4. Integration Layer

API Gateway: The system includes an API gateway to manage communication between the UI, application layer, and data layer. It facilitates the integration of third-party services like ASR APIs and cloud-based storage solutions.

Security and Authentication: This layer handles user authentication and data encryption, ensuring that only authorized users can access sensitive information.

5. Deployment Layer

Cloud Infrastructure: The system is hosted on a cloud platform like AWS or Google Cloud, providing scalability and redundancy. It leverages containerization technologies such as Docker for easy deployment and scaling.

Continuous Integration/Continuous Deployment (CI/CD) Pipeline: The architecture includes a CI/CD pipeline to automate testing, integration, and deployment, ensuring that updates are seamlessly rolled out without disrupting service availability.

6. Maintenance and Monitoring Layer

Logging and Monitoring: This layer incorporates tools for real-time monitoring of the system's performance, error logging, and user activity tracking. It ensures that the system remains operational, and any issues are promptly addressed.

Feedback and Updates: The system includes mechanisms for collecting user feedback and continuously updating the machine learning models and algorithms based on new data, ensuring the system's effectiveness over time.

This architecture is designed to provide a robust, scalable, and secure solution for diagnosing OCD, enabling precise and personalized treatment plans for patients.

3.5 REQUIREMENT GATHERING AND ANALYZING

Requirement gathering and analyzing is the initial stage in developing a software solution to identify the presence, severity, and sub-types of OCD in patients. This stage is critical as it establishes the foundation for the entire project by collecting comprehensive information about the project's needs and constraints, thereby enabling the team to define the project scope effectively.

- **Interviewing Stakeholders:**

  To develop a nuanced understanding of OCD diagnosis, it was essential to engage with a broad spectrum of stakeholders, including mental health professionals, OCD specialists, patients, and their families. These interviews were designed to capture diverse perspectives on the diagnostic process. Stakeholders were asked open-ended questions to allow them to share their experiences with OCD assessment, their thoughts on current diagnostic tools, and their suggestions for improvements. By speaking with mental health professionals, we were able to gain insights into the clinical challenges and limitations of existing diagnostic methods. Patients and their families provided valuable input on their personal experiences with OCD diagnosis, which helped in understanding the practical and emotional aspects of the condition. This holistic approach ensured that the project's requirements were aligned with both clinical best practices and patient needs.

- **Surveys:**

Surveys were distributed to a larger audience, including psychiatrists, psychologists, general practitioners, and individuals who have been diagnosed with OCD. The surveys focused on collecting quantitative and qualitative data regarding the effectiveness of current OCD diagnostic tools, the frequency of use of various scales like Y-BOCS and OCI-R, and the perceived gaps in current diagnostic processes. Additionally, the surveys sought to gather information on the importance of integrating voice analysis and pitch detection in the diagnosis process. This data was invaluable in identifying key areas for improvement in OCD diagnostics, ensuring that the proposed solution would be both innovative and practical.

- **Reviewing Current Literature and Research:**

A thorough review of the existing literature on OCD diagnosis was conducted to understand the strengths and weaknesses of current methodologies. The review focused on studies related to the Yale-Brown Obsessive Compulsive Scale (Y-BOCS), the Obsessive-Compulsive Inventory-Revised (OCI-R), and other relevant diagnostic tools. Special attention was given to research exploring the use of voice analysis and machine learning in mental health assessments. By examining these studies, the project team was able to identify potential opportunities for enhancing the diagnostic process through the integration of technology. The literature review also included an analysis of the latest developments in automatic speech recognition (ASR) and voice pitch analysis, which informed the technical design of the voice analysis component. This comprehensive literature review ensured that the project was grounded in the latest scientific research, positioning it at the cutting edge of OCD diagnostic innovation.

Overall, the requirement gathering, and analysis phase laid a solid foundation for the successful development of a tool capable of accurately identifying OCD presence, severity, and subtypes. Through careful engagement with stakeholders, detailed surveys, and an in-depth review of existing research, the project team ensured that the system would meet both clinical needs and patient expectations.

3.6 WORK BREAKDOWN STRUCTURE (WBS)

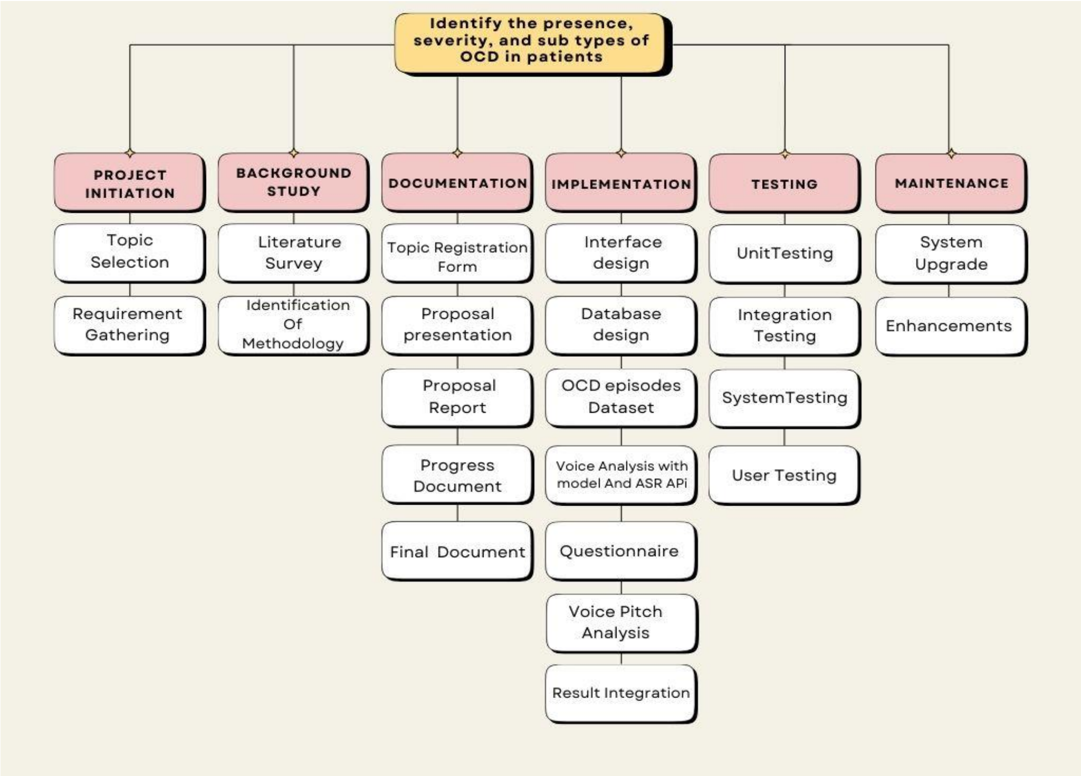


Figure 3: Work Breakdown Structure

3.7 Gantt Chart

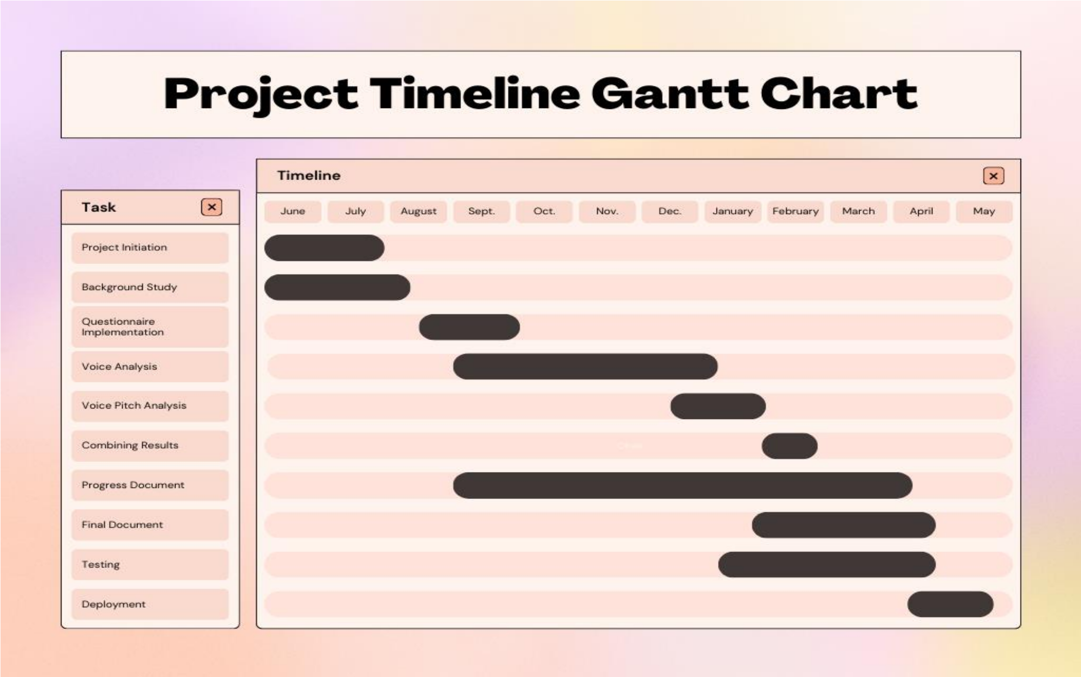


Figure 4: Gantt Chart

4. PROJECT REQUIREMENTS

4.1 FUNCTIONAL REQUIREMENTS AND NON-FUNCTIONAL REQUIREMENTS

- **Functional Requirements:**

1. Dynamic Questionnaire Implementation:

- The system should implement a dynamic questionnaire that includes questions based on the Yale-Brown Obsessive Compulsive Scale (Y-BOCS), Obsessive-Compulsive Inventory-Revised (OCI-R), and custom questions tailored to the specific needs of the application.
- An algorithm should be developed to adjust the order of questions based on the user's responses, ensuring a personalized and accurate assessment.
- The questionnaire responses must be analyzed to determine the presence, severity, and sub-type of OCD in patients.

2. Keyword Detection in Voice Recordings:

- The system must capture and process patient voice recordings where they describe their OCD experiences.
- An Automatic Speech Recognition (ASR) API should be utilized to convert voice recordings into text.
- A machine learning model, such as Support Vector Machine (SVM), must be trained to detect specific keywords in the transcribed text that relate to OCD symptoms.
- The results from the keyword detection should be used to enhance and refine the assessments derived from the questionnaire.

3. Voice Pitch Analysis:

- The system should analyze the pitch fluctuations in patient voice recordings to gain insights into their emotional state and behavior when describing OCD symptoms.
- The Librosa library or similar tools should be used for pitch analysis.
- The results of the pitch analysis should be integrated into the overall assessment, providing a more comprehensive evaluation of the patient.

4. Combining Results for Final Assessment:

- An algorithm must be developed to combine the results from the dynamic questionnaire, keyword detection, and pitch analysis to provide a final diagnosis or severity level.
- The system should use ensemble learning techniques to ensure that the final assessment is robust and accurate.

- **Non-Functional Requirements:**

1. Performance:

- The system must process voice recordings, transcribe text, analyze pitch, and compute the final OCD assessment in a timely manner, minimizing delays.
- Real-time processing is essential for both the questionnaire responses and the voice analysis components.

2. Reliability:

- The system must provide consistent and accurate results, with high reliability in the assessment of OCD presence, severity, and sub-types.
- The accuracy of keyword detection and pitch analysis should be validated through testing.

3. Usability:

- The user interface must be intuitive, allowing mental health professionals to easily administer the questionnaire and review the results.
- Patients should find the system straightforward to interact with, whether they are answering the questionnaire or providing voice recordings.

4. Maintainability:

- The system should be designed with maintainability in mind, allowing for easy updates to the questionnaire, machine learning models, and voice analysis components as new research emerges.

5. Scalability:

- The system must be scalable to handle an increasing number of patients and voice recordings without compromising performance.
- It should be able to process and store large amounts of data as more patients are assessed over time.

6. Security and Privacy:

- Given the sensitive nature of the data being collected, the system must implement strong security measures to protect patient information.
- Compliance with data protection regulations such as GDPR must be ensured.

7. Accuracy:

- The system should be able to accurately transcribe voice recordings and detect relevant keywords related to OCD.
- The accuracy of the pitch analysis in reflecting the patient's emotional state should be validated and reliable.

8. Availability:

- The system must be available for use at any time, particularly during clinical hours, ensuring that assessments can be conducted as needed.

4.2 USER REQUIREMENTS

1. The system must ensure the confidentiality and privacy of student data and assessment results.

2. Compliance with relevant data protection regulations should be a priority.

3. User-Friendly Interface for Clinicians and Patients:
    - The system should provide an intuitive interface for clinicians to easily administer questionnaires, conduct voice analyses, and review combined results.
    - Patients should be able to interact with the questionnaire and provide voice recordings with minimal difficulty.

4. Automated Reporting:
    - The system must automatically generate detailed reports summarizing the results of the OCD assessment, including the presence, severity, and sub-types identified.
    - Reports should be easily exportable for inclusion in patient records.

5. Real-Time Feedback:
   - The system should provide clinicians with real-time feedback during the assessment, allowing for immediate adjustments or follow-up questions based on patient responses.

4.3 SYSTEM REQUIREMENTS

1. Hardware Requirements:

- The system should be compatible with standard desktop and laptop computers used in clinical settings.
- High-quality microphones should be used to capture patient voice recordings for accurate analysis.

2. Software Requirements:

- The system should be built on a stable software platform, capable of handling voice recognition, pitch analysis, and machine learning tasks efficiently.
- It should support integration with cloud-based services for data storage and processing.

3. Network Requirements:

- Reliable internet connectivity is essential for accessing cloud-based APIs and services.
- The system should be designed to function in low-bandwidth environments if necessary, with minimal reliance on real-time data transmission.

4.4 USE CASE DIAGRAM

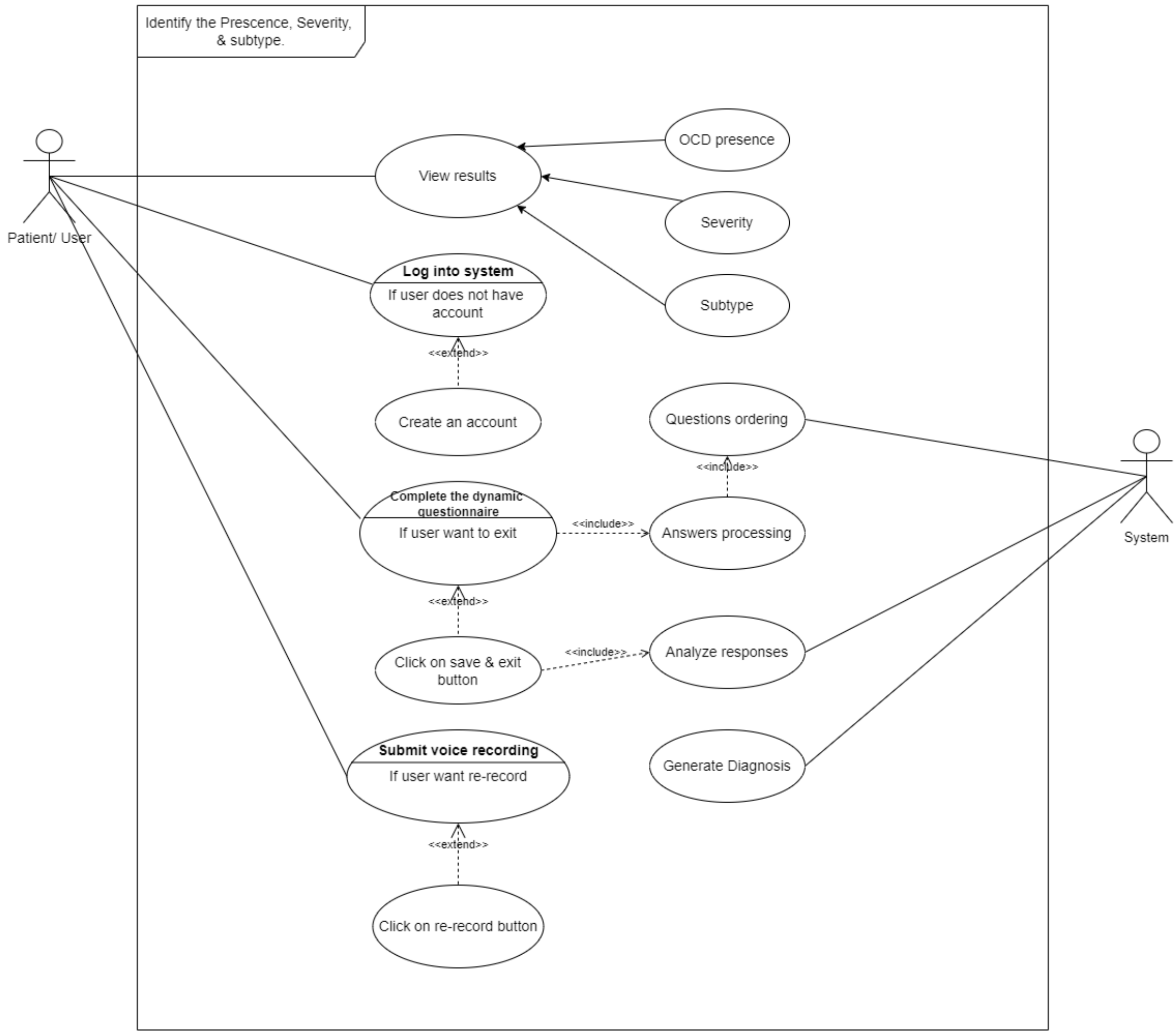


Figure 5: Use Case Diagram

4.5 TEST CASES

1. Dynamic Questionnaire

- Test Case 1.1: Questionnaire Initialization
  Objective: Verify that the dynamic questionnaire initializes correctly with 20 questions.
  Steps:
  Launch the application and navigate to the questionnaire section.
  Observe the initialization of the first question.
  Expected Result: The first question from the Y-BOCS or OCI-R scales should be displayed, and the total number of questions should be 20.

- Test Case 1.2: Dynamic Question Flow
  Objective: Ensure that the questionnaire adapts the flow based on user responses.
  Steps:
  Answer the first question in a specific way that should trigger a different follow-up question.
  Continue answering and observe the question flow.
  Expected Result: The subsequent questions should change based on the user's answers, demonstrating adaptive behavior.

- Test Case 1.3: Data Storage
  Objective: Validate that all questionnaire responses are stored correctly.
  Steps:
  Complete the entire questionnaire.
  Access the database or data storage and review the saved responses.
  Expected Result: All answers should be accurately recorded in the database.

2. Voice Analysis

- Test Case 2.1: Voice Recording Capture
  Objective: Verify that the application captures and stores voice recordings.
  Steps:
  Record a voice sample using the application.
  Save the recording and access the storage location.
  Expected Result: The voice recording should be saved in the specified location without any data loss.

- Test Case 2.2: Speech-to-Text Conversion
  Objective: Ensure that the ASR API accurately converts voice recordings to text.
  Steps:
  Use a voice recording with clear speech and different accents.
  Allow the ASR API to process the recording.
  Expected Result: The transcribed text should accurately reflect the spoken words.

- Test Case 2.3: Keyword Detection
  Objective: Test the keyword detection algorithm on transcribed text.
  Steps:
  Feed transcribed text into the keyword detection system.
  Compare detected keywords with expected keywords based on known OCD terminology.
  Expected Result: The system should correctly identify relevant keywords from the transcribed text.

3. Voice Pitch Analysis

- Test Case 3.1: Pitch Fluctuation Detection
  Objective: Verify that the system can detect pitch fluctuations in the recorded voice.
  Steps:
  Record a voice sample with varying emotional tones.
  Process the recording using the pitch analysis module.
  Expected Result: The system should identify and record pitch variations corresponding to changes in emotional tone.

- Test Case 3.2: Emotional State Analysis
  Objective: Validate the system's ability to infer emotional states from pitch fluctuations.
  Steps:
  Provide a voice sample that conveys stress or anxiety.
  Analyze the pitch fluctuation data for emotional state inference.
  Expected Result: The system should correctly identify emotional states, such as anxiety, based on pitch analysis.

4. Result Integration

- Test Case 4.1: Combining Questionnaire and Voice Analysis Results
  Objective: Ensure the system correctly integrates data from the questionnaire and voice analysis.
  Steps:
  Complete the questionnaire and record a voice sample.
  Allow the system to process both data sets and generate a diagnosis.
  Expected Result: The final output should provide a consistent assessment that incorporates both data sources.

- Test Case 4.2: Final Diagnosis Generation
  Objective: Verify that the system generates an accurate final diagnosis, including OCD presence, severity, and subtype.
  Steps:
  Input test cases with known outcomes into the system.
  Compare the system's diagnosis with expected results.

Expected Result: The final diagnosis should align with expected outcomes, demonstrating the system's reliability.

5. System Performance

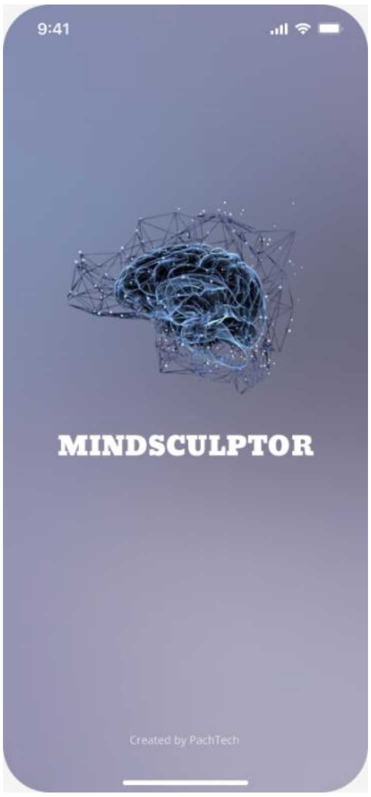
- Test Case 5.1: Load Testing

  Objective: Test the system's performance under a high number of simultaneous users.
  Steps:
  Simulate multiple users accessing and using the system concurrently.
  Monitor system response times and performance.
  Expected Result: The system should handle the load without significant degradation in performance.

- Test Case 5.2: Security Testing

  Objective: Ensure that the system is secure and protects patient data.
  Steps:
  Perform a security audit on the application.
  Test for vulnerabilities such as SQL injection, XSS, and unauthorized data access.
  Expected Result: The system should pass all security tests, with no vulnerabilities detected.

4.6 WIREFRAMES



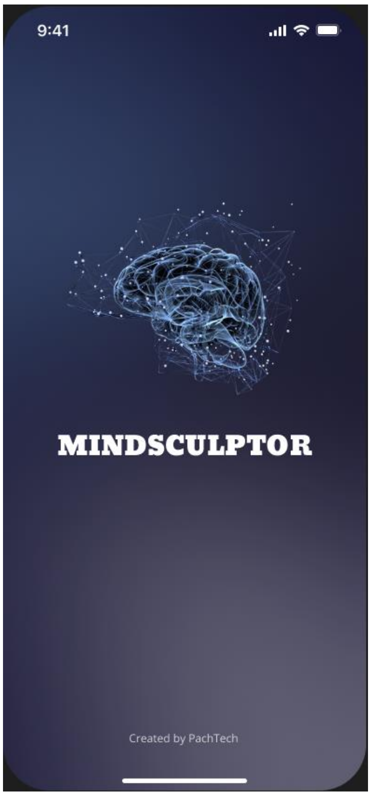
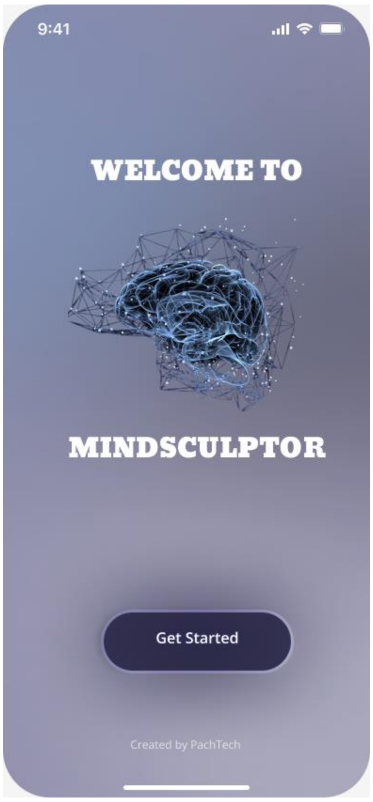


Figure 6: Splash screen (light mode & dark mode)



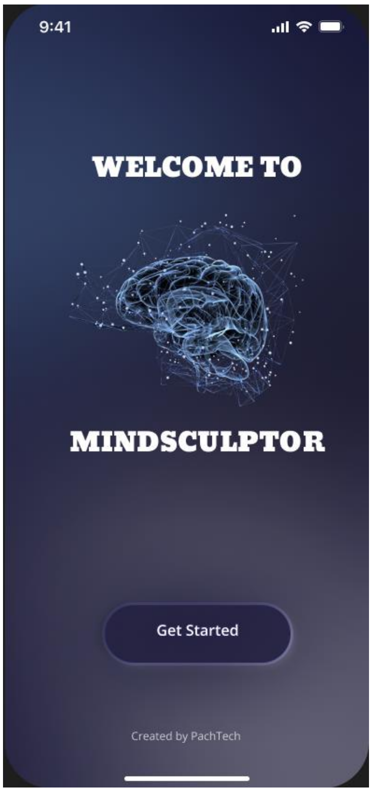
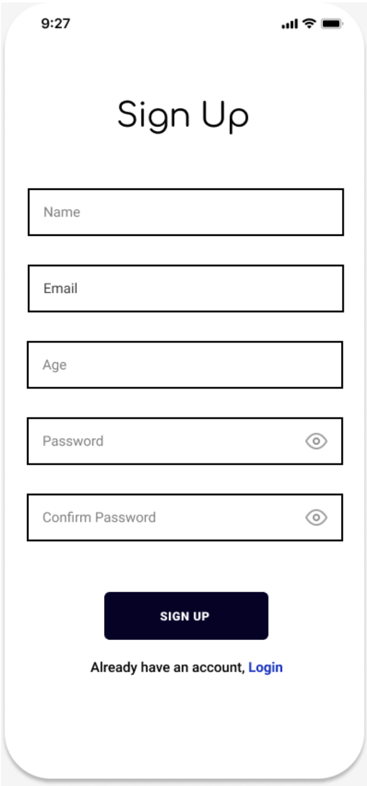


Figure 7: Get started screen (light mode & dark mode)



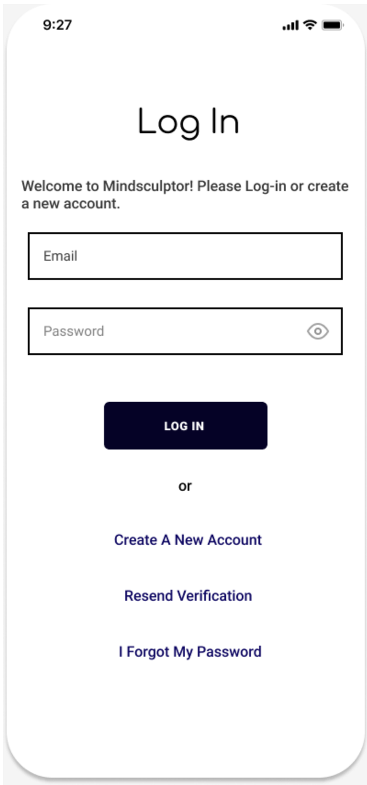
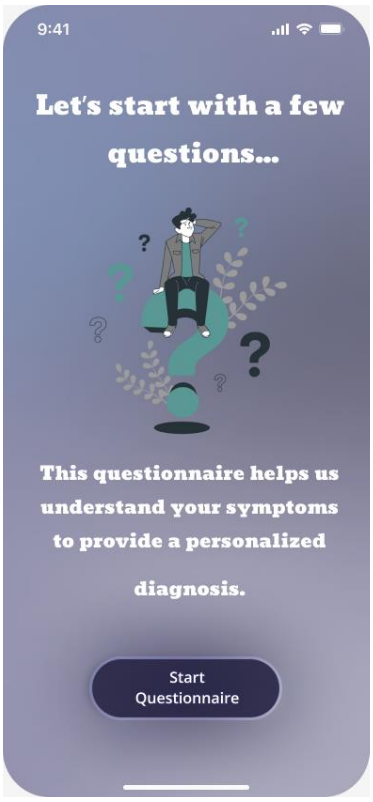


Figure 8: Sign up & Log in screen



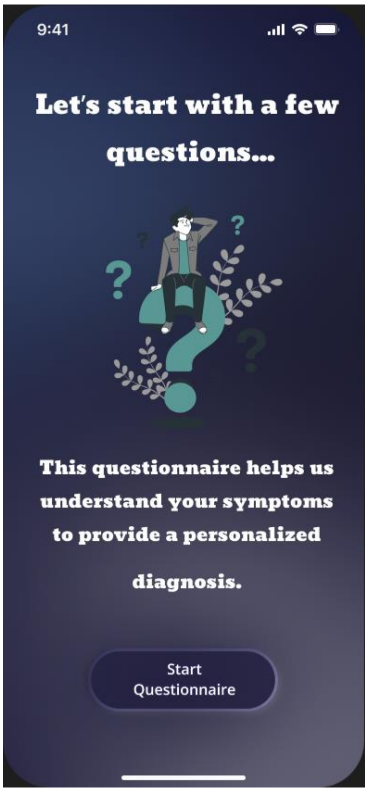


Figure 9: Questions start screen (light mode & dark mode)

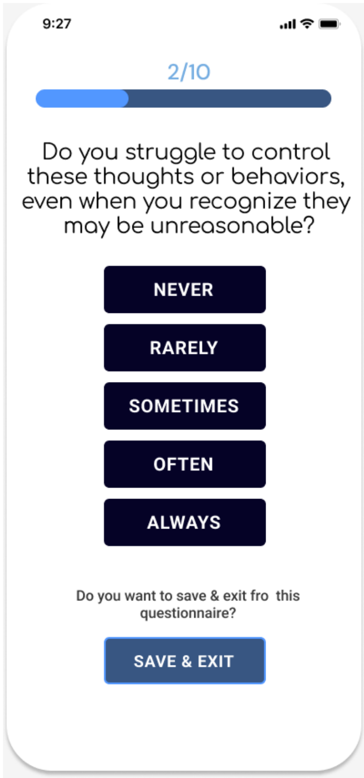


Figure 10: Questions screens

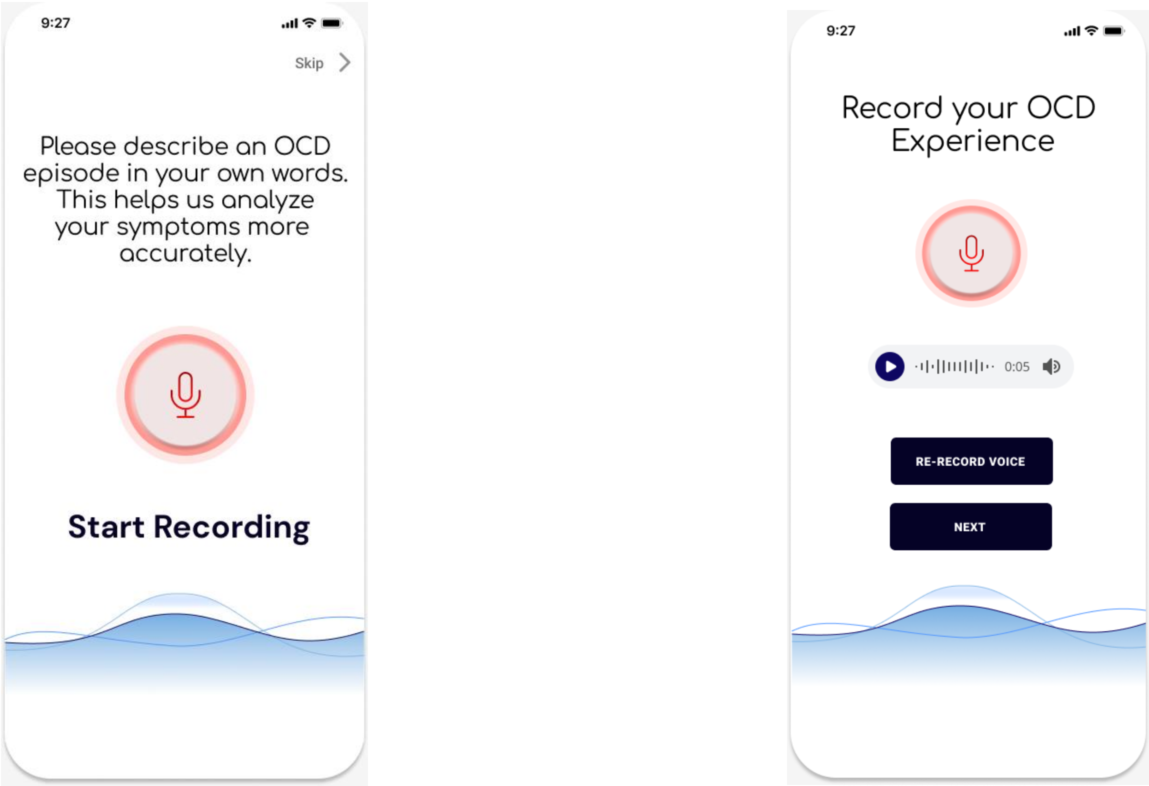


Figure 11: Record OCD experience screens.

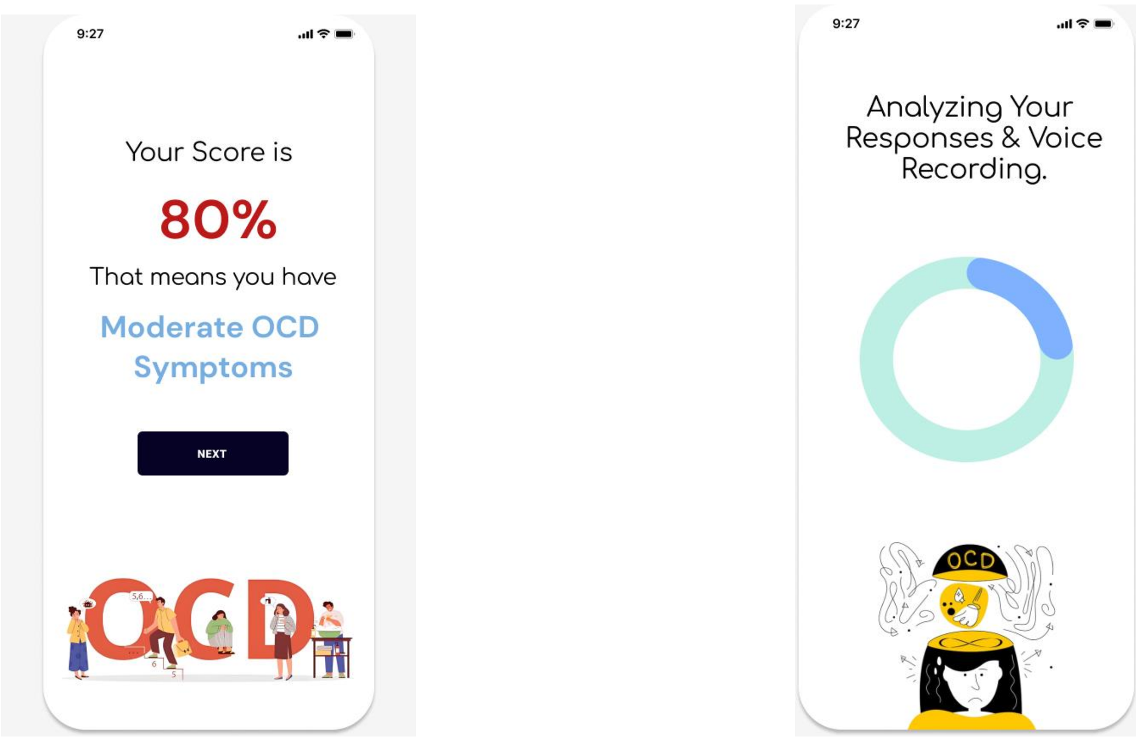


Figure 12: Score & analyzing screens

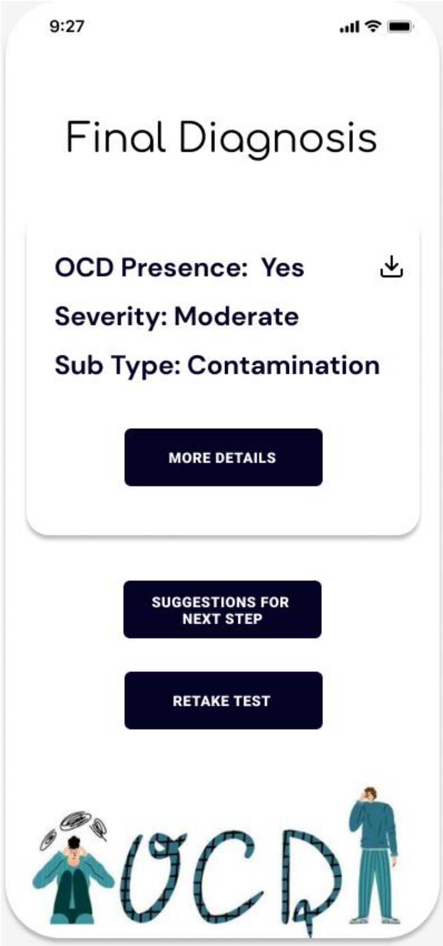


Figure 13: Final diagnosis screen

4.7 TECHNOLOGY AND TOOL SELECTION

Technologies	Techniques	Algorithms
Expo	Speech Recognition	Support Vector Machine (SVM)
React Native	Keyword Detection	Decision Tree Algorithm
Python	Machine Learning	Weighted Scoring Algorithm
Flask	Data Augmentation	
MongoDB	TF-IDF	
VSCode		
Google Colab		
Librosa		
NLTK		
Scikit-learn		
TextBlob		

Table 2: Technology & tool selection

5. BUDGET AND BUDGET JUSTIFICATION

Component	Description	Price
Development Costs	Salaries for developers, designers, and managers	Rs. 300,000 (one-time)
AI & NLP Tools	Licenses/subscriptions for AI and NLP tools	Rs. 10,000 / year
Biometric Analysis Tools	Tools and libraries for biometric analysis	Rs. 5,000 (one-time)
Cloud Services	Cloud storage and computing power	Rs. 15,000 / year
App Maintenance	Ongoing maintenance and updates	Rs. 15,000 / year
Marketing & Promotion	Digital advertising and promotional events	Rs. 25,000 / year
Customer Support	Support staff salaries and tools	Rs. 20,000 / year
Compliance & Security	Data privacy and security compliance	Rs. 7,000 / year
Training & Documentation	Training materials and user guides	Rs. 4,000 (one-time)
Research & Development	Ongoing R&D for feature improvements	Rs. 12,000 / year

Table 3: Budget Table

6. COMMERCIALIZATION

Target Audience

1)Individuals with OCD

- Demographics: Adults and adolescents diagnosed with OCD.
- Needs: Access to effective therapy, personalized treatment plans, and flexible therapy options.
- Pain Points: Stigma, geographical barriers, cost, and infrequent therapist availability.

2)Mental Health Professionals

- Demographhics: Therapists, psychologists, and psychiatrists specializing in OCD and related disorders.
- Needs: Tools for effective patient management, enhanced treatment delivery, and remote therapy capabilities.

- ❖ Pain Points: Limited time for each patient, difficulty in tracking progress, and need for scalable solutions.

3)Healthcare Institutions

- ❖ Demographics :Clinics, hospitals, and mental health facilities.
- ❖ Needs: Integrated solutions for patient care, data management, and evidence-based treatment.
- ❖ Pain Points: Managing large patient volumes, integrating new technologies, and ensuring data privacy.

Marketplace

- ❖ Mental Health Apps Market
- ❖ Digital Therapy Solutions

7. REFERENCES

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8. APPENDICES

❖ Plagiarism Report

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Character count:	47,866
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MINDSCULPTOR: AN OBSESSIVE-COMPULSIVE DISORDER (OCD) EXPOSURE AND RESPONSE PREVENTION (ERP) THERAPY TOOL

24-25J-046

Project Proposal Report

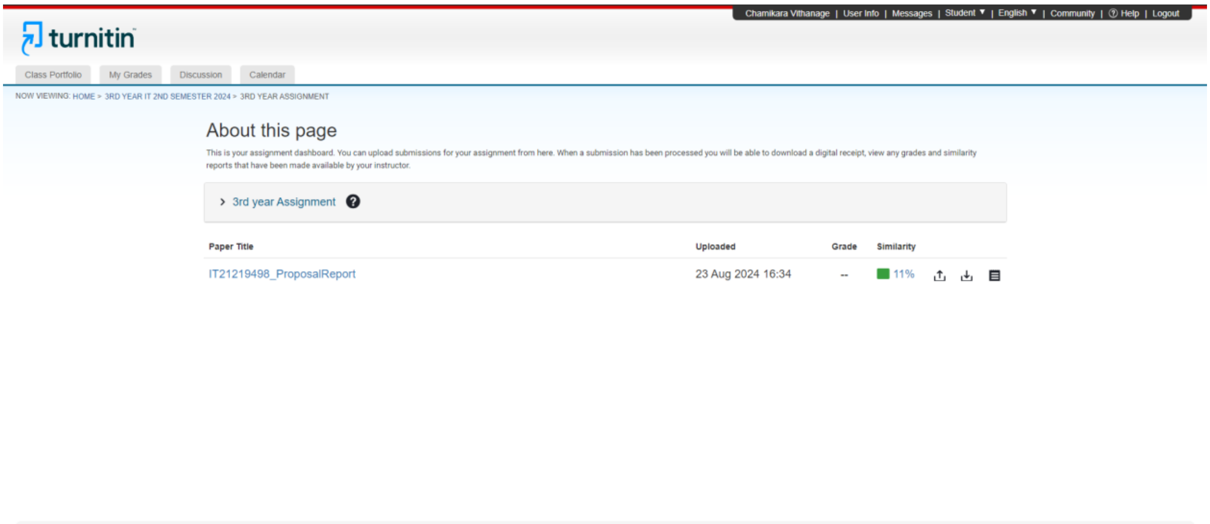
Vithanage C.S.

B.Sc. (Hons) Degree in Information Technology Specialized in Software Engineering

Department of Computer Science and Software Engineering

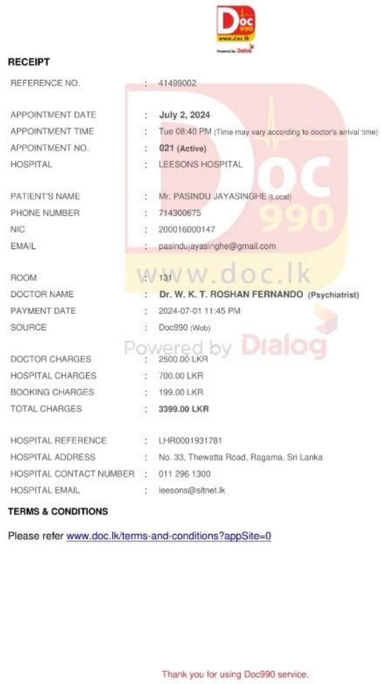
Sri Lanka Institute of Information Technology, Sri Lanka

August 2024



- Meeting with Dr. Roshan Fernando (Psychiatrist):

Our team had the opportunity to meet with Dr. Roshan Fernando, a psychiatrist, to gain valuable insights into the clinical aspects of our research. During this meeting, we discussed the project's objectives and received his expert guidance on understanding the psychiatric evaluation of OCD. A photograph from this meeting is included, alongside the hospital appointment letter confirming our consultation.



RECEIPT

REFERENCE NO.	:	41499002
APPOINTMENT DATE	:	**July 2, 2024**
APPOINTMENT TIME	:	Tue 08:40 PM (Time may vary according to doctor's arrival time)
APPOINTMENT NO.	:	**021 (Active)**
HOSPITAL	:	LEESONS HOSPITAL
PATIENT'S NAME	:	Mr. PASINDU JAYASINGHE (Local)
PHONE NUMBER	:	714300675
NIC	:	200016000147
EMAIL	:	pasindujayasinghe@gmail.com
ROOM	:	131
DOCTOR NAME	:	**Dr. W. K. T. ROSHAN FERNANDO (Psychiatrist)**
PAYMENT DATE	:	2024-07-01 11:45 PM
SOURCE	:	Doc990 (Web)
DOCTOR CHARGES	:	2500.00 LKR
HOSPITAL CHARGES	:	700.00 LKR
BOOKING CHARGES	:	199.00 LKR
TOTAL CHARGES	:	**3399.00 LKR**
HOSPITAL REFERENCE	:	LHR0001931781
HOSPITAL ADDRESS	:	No. 33, Thewatta Road, Ragama, Sri Lanka
HOSPITAL CONTACT NUMBER	:	011 296 1300
HOSPITAL EMAIL	:	leesons@sltnet.lk

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Thank you for using Doc990 service.

- Online Meeting with Miss Sandaru Fernando (Psychologist):

We also conducted an online meeting with our external supervisor, Miss Sandaru Fernando, a psychologist, who provided us with psychological perspectives relevant to our research. Her expertise was instrumental in shaping our approach to the psychological assessment and intervention methods for OCD.