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Abstract

Substance Use Disorder (SUD) present a serious risk to not merely individuals but also organizations, as excessive consumption leads to decreased productivity, health issues, injuries, mental health concerns, unemployment risk, and death. These disorders fall under Sustainable Development Goal 3 - Good Health and Well-Being, Goal 10 – Reduced Inequalities, and Goal 16 – Peace, Justice, and Strong Institutions. Substance Use Disorder encompasses various substance uses, such as substance dependence, drug addiction, and alcoholism. To combat SUD therapy, medication, treatment plans, support groups, and lifestyle modifications can be applied through HealVision. Introducing solutions with the use of aspect-based analysis of textual data for emotion detection to aid the therapist in achieving meaningful results. The application not only supports those with addiction problems but also for their loved ones, providing a platform for mutual support and encouragement.

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List of Abbreviation & Symbols

|  |  |
| --- | --- |
| GPS  SD cards  PCB  App  USB  Hz  GND | Global Positioning Sensor  Secure Digital Memory Card  Printed Circuit Board  Application  Universal Serial Bus  Hertz  Ground |

Chapter 1: Introduction

Addiction is a complicated and formidable issue affecting millions globally. Whether involving alcohol, drugs, or other harmful behaviors, addiction can devastate an individual's physical, mental, and emotional well-being, along with their relationships, work, and overall life quality. While addiction is a widespread issue, access to high-quality addiction treatment can often be limited or expensive. This is where Heal Vision enters the picture. It is an SUD management app designed to offer support to patients and therapists alike. The app provides a variety of features and functionalities aiming to assist users in better understanding their addiction and regaining control over their lives. Whether through addiction evaluation, addiction intensity quiz, health tracking, appointment scheduling, Heal Vision delivers a comprehensive support system for those grappling with addiction.

# Current Work

Within the domain of addiction management and assistance, several notable initiatives are making significant headway. Two key players in this arena are the "I Am Sober" application and the "BetterHelp" platform.

"I Am Sober" stands out as a widely acknowledged mobile app designed to serve as a companion for individuals navigating their recovery journey. The app offers a variety of features, such as daily commitment pledges to maintain sobriety, monitoring progress, and fostering a supportive community of users who share their experiences. Through functions like commemorating milestones and providing personalized motivations, "I Am Sober" aims to instill a sense of accomplishment and encouragement for users dedicated to sustaining sobriety.

Similarly, the "BetterHelp" application provides online counseling services, connecting users with licensed therapists to offer professional support. While not exclusively tailored to addiction management, "BetterHelp" addresses the mental health aspect often intertwined with substance use disorders. The app allows users to conveniently access therapy from their devices, overcoming geographical barriers and making mental health support more readily available.

In tandem with these efforts, Heal Vision recognizes the significance of adopting a holistic approach to addiction management. The app incorporates features such as addiction assessment tools, intensity quizzes, and health tracking to provide users with a comprehensive understanding of their addiction and its impact on their well-being. Additionally, Heal Vision streamlines the scheduling of therapy appointments, establishing a seamless connection between users and therapists to enhance the overall support system.

## Project Vision

Developing HealVision, a user-friendly mobile app utilizing AI to offer tailored assistance and counseling for those grappling with Substance Use Disorders, enabling them to surmount addiction and attain enduring recovery.

## Problem Statement

Substance Use Disorder (SUD) is a chronic disease that affects millions of people worldwide. Traditional therapy for SUD can be expensive, difficult to access, and stigmatizing. As a result, many people with SUD go untreated.

### Problem Statement Domain Overview

Substance Use Disorder (SUD) is a persistent and incapacitating condition characterized by restricted availability of efficient and reasonably priced therapy, frequently impeded by societal stigma and logistical hurdles.

### Problem Elaboration

Traditional therapy is often costly, limited by geography, and burdened by social stigma. The issues are compounded by a lack of awareness, motivation, and social backing. To tackle these challenges, HealVision offers the following solutions:

* Accessibility: The availability of a mobile application accessible anywhere and at any time.
* Affordability: Reduced expenses compared to conventional therapeutic approaches.
* Personalized Assistance: AI-driven tools and therapist support tailored to individual requirements.
* Stigma Mitigation: An anonymous and discreet platform that encourages open communication.
* Motivation and Assistance: Interactive features and online communities fostering active participation in the recovery process.

## Goals and Objectives

HealVision aims to provide accessible, effective, and personalized support to individuals battling Substance Use Disorders, addressing the barriers to traditional therapy.

* Affordable and accessible
* Therapy with AI feedback
* Online support groups and peer coaching

HealVision is helping to break down the barriers to traditional therapy and make it easier for people to get the help they need to overcome SUDs.

## Project Scope

The Heal Vision initiative aims to develop, deploy, and continuously improve an application dedicated to managing Substance Use Disorder (SUD). Its key goal is to establish a robust support system for those grappling with addiction and their therapists. This application will provide a diverse set of features and tools to assist users in comprehending their addiction, controlling its severity, and supporting their path to recovery.

The Heal Vision initiative strives to play a part in the worldwide endeavors to combat addiction. It seeks to provide an affordable, easily accessible, and cutting-edge resolution for both individuals contending with addiction and the professionals aiding them on their path to recovery.

HealVision will be a mobile application featuring:

* Registration and personalized assessments.
* AI-powered chat therapist with emotion detection and feedback.
* Educational modules and relapse prevention tools.
* Appointment scheduling and video sessions with qualified therapists.
* Online support groups and forums for peer connection.
* Data tracking and progress visualization.

Chapter 2: Literature Review / Related Work

In the dynamic landscape of artificial intelligence and natural language processing, the ability to comprehend and interpret human emotions through textual data has become crucial for the development of emotionally intelligent applications. This research journey extensively explores recent progress in emotion detection and sentiment analysis across diverse domains. The literature review encompasses nine papers, each providing valuable insights into methodologies, challenges, and innovations within the field of emotion detection and sentiment analysis. Ranging from interdisciplinary surveys on emotion detection in text to inventive approaches employing deep learning techniques, these papers collectively offer a nuanced comprehension of the intricacies involved in extracting emotions from textual data.



## Emotion Detection of Textual Data: An Interdisciplinary Survey

This paper is a survey and overview of recent progress in text-based emotion detection (TBED). It discusses various methodologies, datasets, limitations, and proposed improvements in the field. The document highlights the use of machine learning techniques for TBED and the importance of labeled datasets for training models. It mentions that the shortage of labeled datasets with multiple emotion labels is a challenge in constructing efficient TBED mechanisms. The annotation process for creating labeled datasets is time-consuming and costly. Another challenge mentioned is the lack of appropriate emotion lexicons. Existing lexicons are not domain-specific and do not consider the context-dependent nature of emotion labels. The paper suggests the construction of domain-specific lexicons for better TBED performance. The document provides a comparison of TBED mechanisms based on their performance ratios, such as F1 score and accuracy. It also discusses the applications of TBED in various domains. In terms of proposed improvements, the document suggests finding the best combination of machine learning techniques and dimension reduction methods for TBED. It emphasizes the need for adequate labeled datasets to conduct such experiments. Additionally, the document mentions the need for domain-specific emotion lexicons and addresses open issues in the field.

## Aspect-Based Sentiment Analysis of Drug Reviews Applying Cross-Domain and Cross-Data Learning

The paper presents a study on aspect-based sentiment analysis of drug reviews using machine learning techniques. The study focuses on predicting sentiments related to overall satisfaction, side effects, and effectiveness of drugs based on user reviews. The dataset used in the study is obtained from two independent webpages, Drugs.com and Druglib.com, comprising a large number of user reviews on specific drugs. The study investigates the transferability of trained models among medical domains and across data sources. The main limitation of the study is the lack of annotated data, especially for distinct aspects, and the difficulty in transferring models across different domains and data sources. The study suggests that more sophisticated features and powerful machine learning models, such as deep learning approaches, could improve the results and facilitate aspect-based sentiment analysis of patient drug reviews.

## Aspect-Based Sentiment Analysis and Emotion Detection for Code-Mixed Review

This study focuses on multi-label classification of restaurant reviews using machine learning and deep learning techniques. The researchers conducted experiments using two scenarios. In the first scenario, they applied problem transformation methods such as Binary Relevance (BR), Label Powerset (LP), and Classifier Chain (CC) with features extracted from unigram, bigram, and a combination of unigram-bigram. In the second scenario, they used deep learning algorithms, specifically Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU), with a self-developed word embedding. The dataset used in the study consisted of 14,103 reviews with sentiment and emotion labels. The results showed that LP and CC performed better than BR in most aspects, and ET achieved the highest score for the "service" aspect. The study also highlighted the imbalanced label distribution in the dataset and suggested the use of data augmentation or sampling methods to address this issue. Additionally, the researchers recommended incorporating other features, such as POS tagging, to enhance the performance of both machine learning and deep learning models.

Limitations of the study include the limited number of annotators and the small number of data samples for certain emotion labels. The researchers also noted that the combination of unigram and bigram features may not be effective if bigram words are infrequently mentioned in the reviews. To improve the classification results, the study suggests considering additional features and addressing the imbalanced label distribution.

## Aspect-based sentiment & emotion analysis with ROBERTa, LSTM

The paper focuses on sentiment and emotion analysis of tweets related to the Ukraine-Russia war using machine learning and deep learning techniques. The authors propose a novel deep-learning approach that combines the Roberta model with Aspect Based Sentiment Analysis (ABSA) and Long Short-Term Memory (LSTM) for sentiment analysis. They collected a large dataset of geographically tagged tweets related to the war from Twitter and analyzed it using the proposed model. The experimental results show that the suggested hybrid model outperforms state-of-the-art techniques with an accuracy of 94.7%.

The method involves data pre-processing to remove redundant tokens and symbols, followed by training and classification using the proposed ABSA-based Roberta-LSTM model. The model efficiently maps tokens into meaningful embedding space using pre-trained Roberta weights and captures long-distance temporal dependencies in the word embeddings using LSTM. The dataset was obtained from Twitter and contains tweets related to the Ukraine-Russia war, collected using hashtags such as #ukraine, #russia, #Putin, #standwithUkraine, and others.

However, some potential limitations could include the reliance on Twitter data, which may not represent the entire spectrum of public opinion, and the challenges associated with sentiment analysis of informal and noisy text data. The improvements include the development of a more accurate and effective sentiment analysis model using the proposed hybrid approach, which outperforms existing techniques. Additionally, the authors highlight the potential for future research to explore other social media platforms and incorporate more advanced natural language processing techniques for sentiment analysis.

## Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey

This paper is a comprehensive survey on Aspect-Based Sentiment Analysis (AbSA), focusing on the challenges and solutions related to Aspect Extraction (AE), Aspect Sentiment Analysis (ASA), and Sentiment Evolution (SE). The methodology involves organizing the survey into sections that define sentiment with respect to aspect, list major issues and challenges, discuss recent solutions, and highlight future research directions. The survey also includes a comparison of existing surveys related to ABSA and SA.

Datasets and performance metrics are mentioned, with reported performance of presented solutions for ASA, such as weakly supervised opinion summarization, supervised aspect rating, and unsupervised word negation. The paper also discusses the use of various datasets, including SemEval 2014 and 2015, TripAdvisor, and oposum dataset (amazon reviews), along with performance metrics like precision, recall, and F1 score. Limitations mentioned include the need for improved personalized summarization for aspect summarization and the challenge of predicting sentiment dynamicity. The paper also highlights the limitations of existing surveys, such as being outdated due to exponential achievements and innovations in recent years.

Improvements include the need for future research directions to improve present solutions, achieve good classification accuracy at aspect-level, predict SE dynamicity, and measure the change of sentiment value with time. The document also proposes the consideration of sub-issues and sub-challenges for resolving major challenges in AbSA, as well as the adoption of cognitive techniques for studying human behaviors through machine intelligence imitation. Overall, the survey provides a foundation for researchers to understand the recent progress in the field of AbSA and formulate general strategies applicable to various scenarios.

## A review on sentiment analysis and emotion detection from text

Sentiment analysis is a technique used to analyze the sentiments of users or authors based on their opinions. It involves extracting features from text, applying machine learning algorithms, and evaluating the model's performance using metrics like accuracy, precision, and recall. The process faces challenges such as informal text, spelling mistakes, and slang, which make it difficult for machines to accurately analyze sentiment and emotion. Researchers have worked on various datasets, including Hindi-English code mixed with emotions, and have used techniques like word vectorization and the Bag of Words approach. Improvements have been made by updating lexicons and incorporating word embeddings to enhance sentiment classification performance.

Sentiment analysis is used to analyze the sentiments of users or authors based on their opinions. The process involves extracting features from text, applying machine learning algorithms, and evaluating model performance using metrics like accuracy, precision, and recall. Challenges in sentiment analysis include informal text, spelling mistakes, and slang, which make it difficult for machines to accurately analyze sentiment and emotion. Researchers have worked on various datasets, including Hindi-English code mixed with emotions, and have used techniques like word vectorization and the Bag of Words approach. Improvements have been made by updating lexicons and incorporating word embeddings to enhance sentiment classification performance.

## The Biases of Pre-Trained Language Models: An Empirical Study on Prompt-Based Sentiment Analysis and Emotion Detection

This paper discusses the methods, datasets, improvements, and limitations of a study on prompt-based sentiment analysis and emotion detection. The study aims to analyze the biases of pre-trained language models (PLMs) and evaluate the utility of prompts in affective computing tasks.

The study uses large annotated emotion and sentiment classification data to evaluate the performance of different PLMs, including RoBERTa, BERT, ALBERT, and Bart. Fine-grained emotion taxonomies are found to be more effective than coarse-grained ones in affective computing tasks. Using multiple word forms of label-words improves performance, with adjective emotion words being more effective than nominal counterparts. PLMs show biases towards certain label classes in fine-grained classification tasks, resulting in weak performance. The variables of label-word selections, Part-of-Speech (PoS) variations, prompt templates, and positions influence the classification results of PLMs. Better label-word selection and prompt engineering methods, as well as ensemble learning, are suggested as potential ways to mitigate biases and improve results.

## Knowledge-enabled BERT for aspect-based sentiment analysis

The paper discusses the use of a sentiment knowledge graph (SKG) to improve aspect-based sentiment analysis (ABSA) using the BERT language representation model. The goal is to incorporate external domain knowledge into the model and provide explanations for ABSA results. The paper presents the methodology, experimental setup, and evaluation metrics used to assess the performance of the knowledge-enabled BERT model. A dataset of online learner reviews is used for evaluation. The limitations of the model are also discussed.

The proposed method involves integrating a sentiment knowledge graph (SKG) into the BERT model for ABSA. The SKG captures the sentiment relations between aspect terms and sentiment words. The model uses the BERT architecture with parameter settings similar to the basic version of BERT. The SKG is added during the fine-tuning phases of the model. The performance of the knowledge-enabled BERT model is evaluated using accuracy, Macro-F1, and F1-score metrics.

The use of the sentiment knowledge graph (SKG) in the BERT model improves the performance of aspect-based sentiment analysis. By incorporating external domain knowledge, the model is able to provide explanations for the ABSA results. The experimental results demonstrate that the knowledge-enabled BERT model produces better token embedding representations and brings improved performance in ABSA.

The model is evaluated using a dataset of online learner reviews collected from MOOC offerings on two Chinese university MOOC platforms. The dataset consists of posts by online learners in different advanced language programming courses. The dataset is preprocessed by separating sentences, segmenting words, and removing stop words. The final dataset includes 13167 sentences with 1692 unique terms. The aspect terms and sentiment terms of the sentences are labeled by term type into two groups: nouns and adjectives. One limitation of the model is the requirement for a consistent vector space to learn the embeddings of words with knowledge from the sentiment knowledge graph (SKG). This can be challenging as words in the text and entities in the SKG are acquired in separate ways. Another limitation is the assumption that the sentiment knowledge graph provides comprehensive domain knowledge. However, there may be limitations in the coverage and accuracy of the knowledge graph.

## Deep learning for Aspect-based Sentiment Analysis

The paper discusses the development and advancements in Aspect-Based Sentiment Analysis (ABSA) using deep learning methods. It mentions that traditional methods for ABSA rely on emotional dictionaries and have limitations such as low precision and the need for continuous updates. Deep learning approaches based on CNN/RNN have been proposed to address these challenges. Several methods and models are mentioned in the paper, including H-LSTM (Hierarchy bidirectional LSTM), PhraseRNN, and Coattention-LSTM network. These models aim to improve sentiment analysis at the sentence and review levels, enhance the representation of target aspects, and address the issue of unfair attention scoring for context.

The paper also highlights the challenges in ABSA, such as domain adaptation, multilingual environments, and imbalanced data. Domain adaptation refers to the transferability of parameters trained in one domain to another. Multilingual environments pose challenges due to word sense ambiguity, language-specific structures, and translation errors. Additionally, the lack of resources for constructing NLP models in many languages contributes to imbalanced data. Datasets mentioned in the paper include SemEval 2014 Task 4 and Twitter for evaluating the performance of different models. The limitations of current DL methods in ABSA are acknowledged, and the need for further research and improvement is emphasized.

Overall, the paper provides an analysis of the recent developments, challenges, and suggestions for future research in ABSA using deep learning methods.

## Literature Review Summary Table

This Table is made for the overall overview of the different research papers that we have studied for the project purpose.

The purpose was to examine the main problem related to the addiction purpose and finding out the suitable datasets and approaches for our AI module usage.

Table 1: Literature Review

The summary of various research on aspect based sentiment analysis

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| No. | Name, reference | Publisher | Year | Methodology | Dataset’s Used | Description |
| 1. | Emotion Detection of Textual Data: An Interdisciplinary Survey | Samira Zad, Maryam Heidari, James H Jr Jones, Ozlem Uzuner | 2021 | Supervised learning (SVM, Naive Bayes, and LSTMs.)  Unsupervised learning (K-means.) | ISEAR, PAN, and MPQA.  Challenge-specific datasets like SemEval. | Each dataset provides text samples labeled with emotions.  Datasets vary in size, domain (e.g., Twitter, news), and annotation complexity.  Challenges: |
| 2. | Aspect-Based Sentiment Analysis of Drug Reviews Applying Cross-Domain and Cross-Data Learning | Felix Gräßer, Surya Kallumadi, Hagen Malberg, Sebastian Zaunseder | 2018 | Predict sentiment for overall satisfaction, side effects, and effectiveness of drugs in user reviews. | Drugs.com & Druglib.com  Content: User reviews  Size: Large  Structure: Unlabeled text reviews | Each review expresses opinions on multiple aspects (satisfaction, side effects, effectiveness) without explicit labeling. |
| 3. | Aspect-Based Sentiment Analysis and Emotion Detection for Code-Mixed Review | Andi Suciati, Indra Budi | 2020 | (ML): BR, LP, CC problem transformation methods  (DL): BiLSTM & GRU deep learning models | 14,103 restaurant reviews  Sentiment & emotion labels (multi-label) | Classify multi-label sentiment & emotion in reviews using both ML & DL techniques. |
| 4. | Aspect-based sentiment & emotion analysis with ROBERTa, LSTM | Uddagiri Sirisha, Bolem Sai Chandana | 2022 | Novel deep learning model: ABSA-based Roberta-LSTM | Large, geographically tagged tweets related to Ukraine-Russia war  Collected using hashtags like #ukraine, #russia, etc. | Analyzes tweet sentiment and emotion using proposed hybrid model.  Data pre-processed to remove noise and symbols.  Model achieves state-of-the-art accuracy (94.7%) |
| 5. | Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey | Ambreen Nazir, Yuan Rao, Lianwei Wu, Ling Sun | 2020 | Challenges and Solutions for AE, ASA, and SE  Comparison with existing AbSA and SA surveys | SemEval,  TripAdvisor, Amazon reviews) | This survey establishes a solid foundation for understanding AbSA advancements and developing universal strategies across different scenarios. |
| 6. | A review on sentiment analysis and emotion detection from text | Pansy Nandwani, Rupali Verma | 2021 | Comparison with existing AbSA and SA surveys | SemEval, EmoBank, EmoTex | This survey also establishes a solid foundation for understanding AbSA advancements and developing universal strategies across different scenarios. |
| 7. | The Biases of Pre-Trained Language Models: An Empirical Study on Prompt-Based Sentiment Analysis and Emotion Detection | Rui Mao, Qian Liu, Kai He, Wei Li, Erik Cambria | 2023 | Applying different PLMs (RoBERTa, BERT, etc.) to annotated emotion/sentiment data | Large, annotated data for emotion and sentiment classification | Study assesses biases and effectiveness of PLMs in affective computing (emotion & sentiment) |
| 8. | Knowledge-enabled BERT for aspect-based sentiment analysis | Anping Zhao ,  YuYu | 2021 | Knowledge-enabled BERT: Integrates a sentiment knowledge graph (SKG) into BERT for ABSA. | Online learner reviews  Preprocessing:  Size: 13167 sentences, 1692 unique terms. | Explores using SKG to improve BERT for ABSA and enhance result explanations. |
| 9. | Deep learning for Aspect-based Sentiment Analysis | Jie Wang, Bingxin Xu, Yujie Zu | 2021 | Models like H-LSTM, PhraseRNN, and Coattention-LSTM is used | SemEval 2014 Task 4, Twitter. | Deep learning advancements in ABSA, highlighted models and their focuses, outlined challenges, and mentioned datasets and evaluation metrics for a concise overview. |

**2.11 Conclusion**

The amalgamation of discoveries underscores recurrent obstacles, such as restricted labeled datasets and the necessity for lexicons specific to particular domains. The application-oriented investigations, ranging from assessments of pharmaceuticals to analyses of geopolitical messages, spotlight a range of difficulties encountered in sentiment analysis. Introducing a practical element, an Emotion Detection-Based Chat Module illustrates the tangible impact of emotion detection in therapeutic environments. To sum up, this expedition offers a glimpse into the present landscape, accentuating enduring challenges and paths for future exploration in the realm of emotionally intelligent AI.

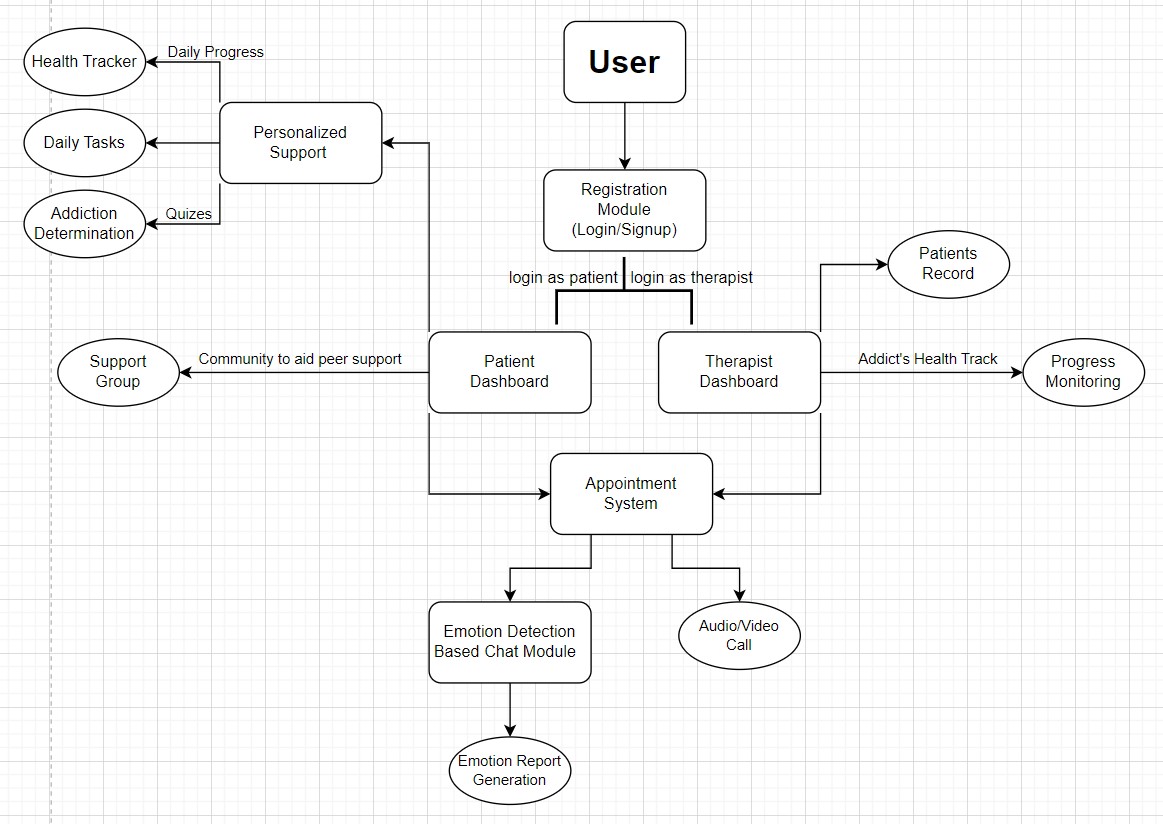
Chapter 3: Proposed Approach and Methodology



## Introduction

The implementation of the proposed mental health application involves several key modules designed to cater to the distinct needs of both patients and therapists. The Registration Module serves as the entry point, enabling users to create accounts or log in, with options to specify their user type. The Patient Dashboard offers a personalized view of progress, integrating features such as daily tracking, personalized support, and access to educational resources. The Personalized Support module tailors resources based on individual needs, encompassing tasks, addiction determination, support groups, and motivational elements. The Therapist Dashboard facilitates monitoring patient progress, direct communication, and appointment management. The Appointment System streamlines scheduling, with integrated reminders and compatibility with virtual platforms. Additionally, the Emotion Detection Based Chat Module utilizes AI to analyze emotional cues in text-based communication, providing therapists with valuable insights.

## Block Diagram



## Registration Module

**Function:**

* Allows users to create new accounts or log in to existing ones.

**Features:**

* Username and password fields
* Option to select user type (patient or therapist)
* Input fields for personal information (name, email, etc.)
* Agreement to terms of service and privacy policy

## Patient Dashboard

**Function:**

* Provides patients with a personalized view of their progress and resources.

**Features:**

* Daily progress tracking (e.g., tasks completed, milestones reached)
* Personalized support options (see below)
* Access to quizzes and educational materials
* Visualization of health data and trends

## Personalized Support

**Function:**

* Offers tailored resources and guidance based on individual needs.

**Features:**

* Daily tasks and habit-building activities
* Addiction Determination
* Support groups or forums for peer interaction
* Recommendation of relevant tools and strategies
* Motivational messages and reminders

## Therapist Dashboard

**Function:**

Allows therapists to monitor patient progress, provide feedback, and manage appointments.

**Features:**

* Patient progress overview
* Access to patient records and data
* Ability to communicate with patients directly
* Appointment scheduling and management tools
* Tools for generating reports and insights

## Appointment System

**Function:**

* Facilitates scheduling and management of virtual or in-person appointments between patients and therapists.

**Features:**

* Calendar view for availability
* Booking and rescheduling options
* Reminders for upcoming appointments
* Integration with video conferencing or messaging platforms

## Emotion Detection Based Chat Module

**Function:**

* Uses AI technology to analyze text-based communication for emotional cues.

**Features:**

* Emotion detection during chat sessions
* Generation of emotion reports for therapists
* Potential for tailored responses or interventions based on detected emotions

## Requirements & Constraints

**Required Technologies and Tools:**

**Framework:** Flutter

**Language:** Dart

**Database:** Firebase (including Authentication, Firestore, and potentially other services as needed)

**Constraints:**

**Corporate or Regulatory Policies:**

* Adhere to HIPAA compliance for handling sensitive health data.
* Implement robust security measures to protect user privacy.
* Obtain user consent for data collection and sharing.

**Hardware Limitations:**

* Optimize performance for diverse mobile devices with varying processing power and memory constraints.
* Consider network connectivity issues for offline functionality or data caching.

**Interfaces to Other Applications:**

* Integrate video conferencing platforms for virtual appointments.
* Explore potential integrations with wearable devices or health tracking apps.

**Parallel Operations:**

* Handle concurrent user interactions and data updates efficiently.

**Language Requirements:**

* Use Dart for all application logic and UI development.

**Communications Protocols:**

* Securely transmit data between the app and Firebase servers using HTTPS.

**Security Considerations:**

* Implement authentication and authorization mechanisms.
* Protect sensitive data at rest and in transit using encryption.
* Regularly conduct security audits and vulnerability assessments.

**Design Conventions and Programming Standards:**

* Adhere to Flutter's best practices and coding guidelines.
* Ensure code readability and maintainability for future updates.

## Conclusion

In conclusion, the outlined modules collectively create a comprehensive mental health application that addresses the diverse needs of patients and therapists. The Registration Module ensures a seamless onboarding process, while the Patient Dashboard and Personalized Support features contribute to a holistic and tailored patient experience. The Therapist Dashboard empowers clinicians with tools for efficient patient management and engagement. The Appointment System adds a practical dimension by simplifying scheduling and enhancing communication. The integration of the Emotion Detection Based Chat Module introduces a novel aspect, leveraging AI to discern emotional nuances in communication, thus enriching the therapeutic process. As the application progresses, continuous refinement and optimization of the backend algorithms supporting these modules will be crucial to ensure accuracy, efficiency, and a positive impact on mental health outcomes.

Chapter 4: Executed Work

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Concisely list down the principle milestones and associated deliverables that must be achieved  in order to accomplish the project objectives. Add more rows if required.   |  |  |  |  |  | | --- | --- | --- | --- | --- | | **S.No.** | **List of project milestones** | **Deliverable(s)** | **Expected months to complete** | **Percent Completed** | | 1. |  | Requirements Engineering |  |  | | 2. |  | Survey of healthcare professionals |  |  | | 3. |  | Designing UI of the application |  |  | | 4. |  | Analyzing and researching various datasets as well as models of aspect-based Analysis for emotion detection |  |  | | 5. |  | Deployment of UI on the development tool and training model |  |  | |  |  | Deploying Model and deploying backend |  |  | |  |  | Full Complete Integration and Testing |  |  |   Prototype  Dataset Selection  Model Selection  Model Training  Database Creation  Survey of healthcare professionals |

## Remaining Work:

Describe in details the plans to execute remaining works. The sequence, as already described above in the table should be followed as possible.

## Gantt chart

A detailed and neat Gantt chart should be **attached**. It may be landscape but it should not have any page number, header and footer. Gantt chart should be listing all the major and minor activities, **indicating executed and remaining tasks**, along with the time spans. Make sure that the Gantt chart is reflecting all the project milestones

# References

**This chapter is mandatory.** List all important sources of information which have been consulted for this project.

# Appendix

## Appendix A: Guidelines

This section should include all supporting information from the project that was not included in the body of the report.  You should include surveys, complex statistical calculations, certain detailed tables and other such information in an appendix.  The information presented in this section is important to support the work presented in the body of the report but would make it more difficult to read and understand if presented within the body of the report.

Cite the appendix items in the report narrative (write "see Appendix A") and organize appendices (e.g., Appendix A, Appendix B,

Any tables, figures, forms, or other materials that are not totally central to the analysis but that need to be included are placed in the Appendix.

# Formatting Guidelines

This document also serves as style guide for final year project reports. In order to give a similar high-quality appearance to all final year software project reports this template uses a collection of predefined Microsoft Word formatting styles. **These styles should be used without modification or replacement.** Font in the document is ***“Time New Roman”.*** This template provides following styles:

* **Title** – the main title style
* **Title2** – the subtitle style
* **Body Text** – style for paragraphs
* **Caption** – the style for a figure or table caption
* **Table Description** – the style for description of table, it must be added after caption.
* **Figure Description** - the style for description of figure, it must be added after caption.
* **Code** – the style for program source code

**int x** = 10; // Writing important code

* **Table Header Row** – Style for the header row of table
* **Table Grid** – the style for the data rows in the tables
* **Reference** – The style for references
* **Bullets** – The style for the bullet lists
* **Numbered** **List**– Style for numbered lists

All Heading styles with different level numbers are listed below.

# Heading 1

## Heading 2

### Heading 3

#### Heading 4

##### Heading 5

###### Heading 6

Heading 7

Heading 8

Heading 9

## Tables and Figures

Tables and figures should be centered horizontally. The caption button should be used to insert caption for both the figures and tables. All figures and tables must be numbered properly. Always refer to tables and figures according to their numbers. A table or figure can be cited as follows: ‘see Table1’ or ‘as shown in Table1’. The caption of table should be centered above the table and figure caption should be centered below the figure. Place the tables/figures close to their reference. Use “Table Header Row” and ‘Table Grid’ style for table’s header and data rows respectively. It is compulsory to provide brief description of table/figure after its caption. Styles for table and figure descriptions are “Table Description” and “Figure Description” respectively.

Press **Ctrl + Shift + S** to see list of styles mentioned above. Figure 1 shows the Apply Style window displaying the list of styles. Select any text then press **Ctrl + Shift + S**, the Apply Style window will show you the current style applied on that text and if required, you can change the style by selecting any other style from the “Style Name” dropdown.

A screenshot of a computer

Description automatically generatedThis is brief description of above figure.

Figure 2: List of Styles

Table 2: This is Sample table caption

This is brief description of following Table.

|  |  |  |  |
| --- | --- | --- | --- |
| Header row | Header row | Header row | Header row |
| Row1 col1 | Row1 col2 | Row1 col3 | Row1 col4 |
| Row2 col1 | Row2 col2 | Row2 col3 | Row2 col4 |

Table 3: This is Sample table caption

This is brief description of following Table.

|  |  |  |  |
| --- | --- | --- | --- |
| Header row | Header row | Header row | Header row |
| Row1 col1 | Row1 col2 | Row1 col3 | Row1 col4 |
| Row2 col1 | Row2 col2 | Row2 col3 | Row2 col4 |

## Equations

Use equation editor to write equations in this report. Use last button of the custom tool bar to invoke equation editor. Similar to tables and figures, equations should also be aligned centered horizontally. Number all equations and insert them in parenthesis. Below is a sample equation and its reference number. An equation can be referenced like this: ‘it is clear from (1)’.

 (1)

## Header/Footer

Notice the headers in this document, before Introduction (i.e., the main content of this document) page numbers are in roman numerals. The page numbers of the actual content start with Arabic numerals i.e. 1, 2, 3 and so on. All of the **odd numbered pages** contain title of your project while the **even numbered pages** contain the section heading (i.e., chapter’s name) in the headers.

## Other Formatting Guidelines

* Keep 2-4 GUIs in one page. Consume as much space as possible. Do not leave most of page blank unnecessarily.
* Do not break tables (or use cases) in multiple pages unless the table is too large to fit in one page.
* Re-arrange the content i.e., text, images and tables properly to meet above two guidelines.

## References

Always refer to the source of information by inserting the reference number in square brackets like this [5]. The reference numbers can either be added at the end of the sentence or within the sentence without changing the punctuation of sentence. A reference can also be cited as follows: ‘as Ruskey [2] mentioned’. List each source only once on your reference page.

A text on a page

Description automatically generated

Figure 3: IEEE Reference style

This figure represents the styling information for adding references in IEEE format

**Following is a list of sample reference for various type of sources in IEEE format.**

1. P.M. Morse and H. Feshback, *Methods* of *Theoretical Physics*. New York: McGraw Hill, 1953. **//Format for Book**
2. S.K. Kenue and J.F. Greenleaf, “Limited angle multifrequency deification tomography,” *IEEE Trans. Sonics Ultrason*., vol. SU-29, no. 6, pp. 213-2 17, July 1982. **//Format for Journal Article**
3. B. Tsikos, “Segmentation of 3-D scenes using multi-modal interaction between machine vision and programmable mechanical scene manipulation,” Ph.D. dissertation, Univ. of Pennsylvania, BCE Dept., Philadelphia, 1987. [Add if applicable: University Microfilms, Inc., University of Michigan, Ann Arbor, Michigan.] **//Format for Dissertation or thesis**
4. R. Finkel, R. Taylor, R. Bolles, R. Paul, and J. Feldman, “An overview of AL, programming system for automation,” in *Proc. Fourth Int. Joint Conf Artif. Intell*., pp. 758-765, Sept. 3-7, 1975. **//Format for Proceedings paper**
5. “Technology threatens to shatter the world of college textbooks, *The Wall Street Journal*, vol 91, pp. Al, A8, June 1, 1993. **//Format for Newspaper article**
6. R. Cox and J. S. Turner, “Project Zeus: design of a broadband network and its application on a university campus,” Washington Univ., Dept. of Comp. Sci., Technical Report WUCS-91-45, July 30, 1991. **//Format for Technical Report**
7. M. Janzen, *Instant Access Accounting*. Computer software. Nexus Software, Inc IBM-PC, 1993. **//Format for** **Software**
8. Fuminao Okumura and Hajime Takagi, “Maglev Guideway On the Yamanashi Test Line,” *http://www.rtri.or.jp/rd/maglev2/okumura.html*, October 24, 1998. **//Format for** **World Wide Web** (give author and title if named)
9. “AT&T Supplies First CDMA Cellular System in Indonesia,” http://www.att.com/press/1095/951011.nsa.html, Feb 5, 1996. **//Format for World Wide Web**