International Journal of Computational Science and Engineering Research
ISSN: XXXX- XXXX(Online) , http://www.ijcser.com/
Regular Issue , Vol. 2, Issue. 1 (January - March), 2025 , Pages: 23 - 30
Received: 17 January 2025 ; Accepted: 28 April 2025 ; Published: 14 May 2025
Research Paper , https://doi.org/10.XXX/XXXX.XXXX.XX.XXXX

Cognitive Behavioral Therapy for Sentimental Analysis using Artificial Intelligence

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Abstract: In today's world humans present their opinions in social media , every day a large amount of text data is dumped ,these user text is used to Train a CBT model to classify emotions. Cognitive Behavioural Therapy (CBT) is a widely applied, proof-based practice to address human mental health problems using structured interventions. CBT incorporates advanced AI and deep learning techniques to enrich the CBT process. For classifying user-generated text into specific emotional categories based on analyzing user intent, the CBT Model has utilized NLU models like BERT, RoBERTa. It uses datasets from Kaggle , Reddit, for emotion detection. The CBT model now generate response using XLNet based on user intent and provide a positive response to lead a healthy life .while existing model only classify where the user input text is depressed or Not Depressed, but proposed model not only classify user input but also provide suggestions to make users mental health stable. This intervention helps in considering AI is more comfortable and provide insight suggestion compared to psychotherapists.

Keywords: Cognitive Behavioral Therapy (CBT), Data Augmentation, Sentiment Analysis, Acceptance and Commitment Therapy , Text Classification, Phobias.

1. Introduction

Cognitive is a human internal brain thinking emotion ,that include thoughts, feelings, ideas and other emotions they go through in daily life activities. Cognitive Behavioral Therapy (CBT) is structured approach to psychotherapy that aims at solving mental health problems. CBT centers its core on the understanding and modification of how thoughts, emotions, and behaviors interplay for the development of healthier cognitive and behavioral health. During such rapid evolution, it's indeed influenced by so much development within psychology and technology that it is one of the most widely used and researched method in mental health care. Recent technological developments have expanded CBT's reach even more, by introducing such as AI-driven mental health Chatbots and synthetic data generation for emotion detection. AI in mental health care has brought about new scope and opportunities for the delivery of CBT. The point out the emergence of health counseling dialogue systems based on behavioral medicine ontologies, which have thus enabled the use of developing interactive and reusable framework approaches to therapeutic interventions[7].

The mentioned systems, hence laid a basis for infusing mental health care environments with AI technologies, thus intensifying structured, context-aware suggestions and enacting user involvement. The integration of NLP and AI into CBT is a step toward filling the gap in accessibility when it comes to mental health care. The use of chatbots powered by NLP to administer CBT interventions as well as to monitor mental health [4] [5] from a distance. These AI-driven systems not only provide personalized support but also ensure scalability and availability, making mental health care accessible to a wider audience. Similarly,[2] showcased the integration of CBT techniques with AI Markup Language (AIML) to develop mobile chatbot psychologists, demonstrating how AI-enabled tools can simulate human-like empathy and understanding in therapeutic settings. One of the greatest challenges in adopting CBT is the detection and management of sophisticated mental health problems, such as suicidal ideation.

Developing a new concept of socially aware synthetic data generation through LLMs to improve the detection of suicidal ideation [1]. Through the creation of artificial datasets, their method solves the problem of scarcity of data and ensures sensitive information related to mental health is approached ethically. This shows the promise of AI in enhancing the specificity and sensitivity of identifying individuals at risk, which is very tough in suicide prevention. Integration of CBT with AI is not an easy task. As highlighted by [3], an exhaustive review of AI applications in mental health care shows the need of interdisciplinary collaboration to address the issues of data privacy, ethical AI, and bias in algorithms. These technologies are developed taking into consideration the human-centric design principles so that AI systems work effectively, are inclusive, and empathetic.

A substantial amount of research supports CBT's success with insomnia as an identifiable and well-researched target for such intervention, systematically reviewed and conducted a meta-analysis of randomized controlled trials to assess the effectiveness of CBT-I in the workplace [8]. The evidence established the favorable impact of CBT-I on sleep health, where sleep quality improves and work-related stress is diminished. In parallel, [9] presented economic benefits of CBT-I among adults by offering a better health outcome with minimal expense. These studies highlight the growing importance of CBT in clinical and non-clinical settings, thereby demanding further development and integration of CBT in diverse therapeutic settings.

2. Literature Survey

Ghanadian et al. presented the need of socially apprehensive stoner data generation to enhance suicidal creativity discovery with large language models(LLMs). Their work says the significance of effective data generation ways to overcome data insuffiency in internal health exploration, enabling more precise and compassionate AI- driven interventions [1]. Omarov et al. combined Cognitive Behavioral remedy with AIML, creating an AI- enabled mobile psychologist chatbot this study represented how a simple chatbot was suitable to produce a scalable and accessible and more individualized tool to deliver CBT [2] to communities depressed in relation to such an intervention.

Mittal et al. gave detailed feedback of the operations of artificial intelligence in internal health care, emphasizing the part of AI in transubstantiating the delivery of CBT. They talked about the integration of NLP and machine literacy for tasks similar as emotion identification, remedy delivery, and internal health monitoring [3]. Gupta et al. proposed a chatbot designed for internal health using NLP ways. This exploration concentrated on the use of a chatbot for time-sensitive, contextually applicable responses, indicating that AI may help condense more traditional CBT ways [4].

Rani et al. developed a internal health bot that combined CBT principles with remote health observing capabilities. Their work explains how AI and CBT can be combined to give both remedial interventions and nonstop health shadowing for druggies to lead a healthy life [5]. Kwak et al. proposed a videotape event recognition frame grounded on scripts, pressing its prospects of operation in internal health. The work concentrated on constraint inflow ways to understand the geste and environment of druggies; hence, it well rounded the CBT system [6].

Bickmore et al. proposed a applicable frame for health comforting dialogue systems grounded on a behavioral drug ontology. This early work laid the foundation for integrating structured ontologies into AI- driven remedial tools, enhancing the contextual applicability of CBT interventions [7]. Takano et al. performed a methodical review and meta- analysis on the effectiveness of CBT for insomnia in workers. Their results showed that CBT is effective in enhancing sleep health, therefore making it applicable in different disciplines [8]. Natsky et al. delved the profitable effectiveness of CBT for grown-ups with wakefulness (CBT- I). Their review was methodical in nature and called attention to the value for plutocrat associated with CBT I, a enough good case for promoting this treatment far and wide [9].

Fiske et al. excavated into the ethical counteraccusations of using embodied AI for psychotherapy. They raised critical questions about trust, empathy, and mortal connection in AI- driven CBT, furnishing a roadmap for addressing these challenges [10]. Grodniewicz and Hohol linked three major challenges in developing AI- driven digital therapists ethical AI, personalization, and societal acceptance. Their study highlights the obstacles to spanning AI- grounded CBT systems while emphasizing the need for mortal-centric design [11]. Hulliyah et al. proposed an emotion classifier- grounded chatbot through the use of Indo BERT-Lite. The purpose was to make better internal health support chat bots using language-specific models to present culturally applicable CBT interventions [12]. Liu et al. developed a parameter-effective fine- tuning language model for Chinese patent drug instructions named CPMI-Chat GLM. similar styles are relatively feasible for use in CBT, particularly in multilingual or sphere-specific scripts [13].

Doan et al. have used an effective fine tuning approach to achieve large language models for Vietnamese chat bots. therefore, the result highlights the substance of localization that needs to make AI- driven tools of CBT accessible to broader populations [14]. Hu et al. presented Low- Rank adaption is a parameter effective fine- tuning system of big language models which has been employed by the systems on CBT towards the deployment in a resource-scarce region for AI- supported internal health conditions [15].

Chavan et al. generalized the LoRA frame for parameter-effective fine- tuning. Their exploration gives an sapience into the optimization of AI models for scalable and customizable delivery of CBT [16]. He et al. surveyed present operations of large language models in internal health and proposed a cerebral generalist AI frame. The authors concentrated on the inflexibility of LLMs to break different internal health problems, similar as the delivery of CBT [17]. Chesney et al. performed a meta- review of the pitfalls of all- cause and self-murder mortality in individualities with internal diseases. Their findings bring to the fore the need for developing AI- driven CBT systems to address the internal health extremity and give timely interventions[18].

3. Existing System

The system automatically determines if a text shows signs of depression. It starts with collecting raw text data from sources like social media posts, medical records, patient journals, or survey responses. The quality and variety of this data are crucial for accurate analysis. After collection, the text undergoes processing to clean it by removing unnecessary characters such as punctuation, numbers, and special symbols.

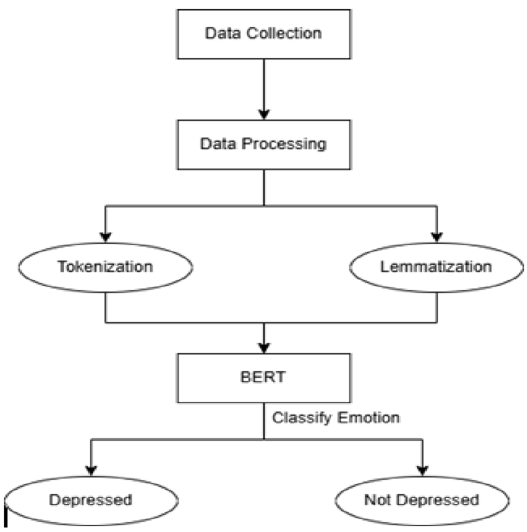

Fig 1. Internal Operational Working Mechanism

This step also deals with missing information and converts all text to lowercase for consistency, preparing it for further analysis. The next step is tokenization and lemmatization. Tokenization breaks the text into individual words or tokens, allowing algorithms to analyze the text at the word level. Lemmatization then reduces words to their base forms; for instance, "running," "runs," and "ran" become "run." This standardizes the text, enhancing the accuracy of the analysis. The processed text is then input into a deep learning model called BERT (Bidirectional Encoder Representations from Transformers). BERT generates contextualized word embeddings by considering the surrounding context of each word, capturing subtle meanings and relationships. This understanding is essential for identifying emotional cues and language patterns linked to depression. Finally, the BERT model classifies the emotion in the text, determining whether it indicates signs of depression.

4. Research Work

The Proposed System chatbot designed to have conversations that feel natural and understanding. First, the chatbot receives the user's message as Input Text. This message then goes through a "Data Preprocessing" stage. In this stage, the chat bot cleans up the message by removing unnecessary parts like extra symbols and fixing any missing words. It also makes sure all the text is in the same format for easier processing. After cleaning, the message goes through Emotion Classification. This is where powerful AI models like BERT and DistilBERT come into play. These models analyze the message to figure out the user's emotions, such as happiness, sadness, anger, or frustration. Understanding these emotions is key to creating helpful and appropriate responses.

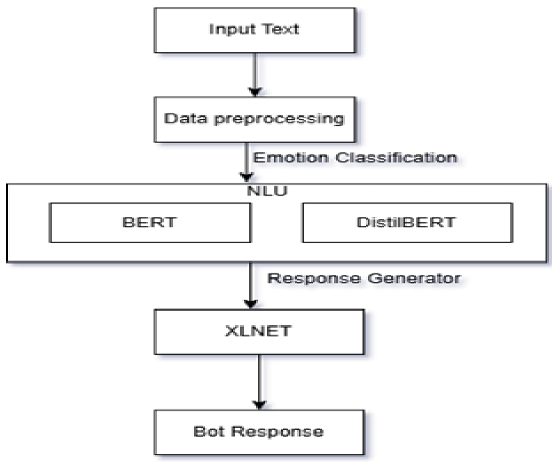

Fig 2. Working Flow

The identified emotions then guide the Response Generator. This part uses a special AI model called XLNET, which is very good at understanding and creating human-like text. XLNET considers the user's emotions and the entire conversation to generate responses that are not just informative but also supportive and relevant to how the user feels. Finally, the Bot Response is shown to the user, completing the conversation. This system uses a combination of advanced AI techniques and sophisticated language understanding models to create a chatbot that can understand and respond to user emotions in a way that feels natural and engaging, just like a human conversation.

A. ALGORITHM

The AI bot response is generated to the user based on the user input text. Firstly Dataset to embedded to the directories for performing Data preprocessing techniques. These include synonym replacement ,text removal for easy identification of emotion by the AI bot for generating the healthy suggestions. It helps in categorizing sentiment of the user based on inserted text then it classify the emotion as positive negative using BERT and RoBERTa models. Then based on the user intent response is generated to provide healthy suggestions to avoid negative intentions in users.

Step1: Firstly user enter a text message T with a sequence of words w. where w_i is the i-th word in the sentence.

$$T=\{w_1,w_2,\ldots,w_n\}$$

Step2: For each word wi in T perform POS tagging where pi is the part-of-speech tag of wi, Retrieve a set of synonyms $S(w_i)$ using a data, where sj are the synonyms of wi that match the same part of speech pi.

$$POS(w_i)= P_i$$

$$S(w_i)=\{s_1,s_2,\ldots s_m\}$$

Step3: Now the BERT model Classify sentiment based on the vocabulary replacement and DistilBert for sentiment categorization into positive, Negative , Neutral. The sequence of words $S(w_i)$ passed to Bert model to classify the text ,embedding the s_i to e_i and Bert processing is done.

$$H_i=BERT(e_i)$$

Step4: Now the Ai Bot would generate responses based on the input text classification ,these responses are generated from the dataset intents and responses y are the response data , and the conversation flow would continue by providing suggestions based on the emotions.

$$P(y_i \mid T_{input},y_1,\ldots y_{i-1})=Softmax(W.h_i+b)$$

$$T_{response}=\{y_1,y_2,y_3,\ldots.,y_m\}$$

B. Implementation

The Dataset is used to train a model for generating responses based on user input text. Firstly a AI framework is created by choosing a online Platforms like RASA to design a bot that perform as questioning and answering CBT model. The data is stored in the directories when user interact with the model it checks the dataset for word matching like synonym matching then it would generate a emotion based on user input and then give suggestions based on emotion and thoughts that are user going through, it helps the user for effective interaction with the AI bot and present all the emotions and get a useful suggestions. Twitter and Instagram are big platforms for the user thoughts , emotions , and feelings.

Social Media Sentiment Analysis Dataset: The social media sentiment analysis dataset is of great value as it analyzes the emotions and sentiments portrayed across different platforms of social media like Twitter, Facebook, and Instagram. It performs a critical function in tasks like sentiment analysis, opinion mining, and emotion detection using Natural Language Processing (NLP).

This dataset contains diverse posts and comments from users classified into sentiment labels like positive, negative, and neutral, thus making it really useful for a supervised learning task targeted at the classification of sentiments. Generally, the dataset usually contains several vital attributes, the most important one being the content of the post, which becomes the primary source of data used in the context of sentiment analysis. It also includes the timestamp of when the post was made, offering valuable insights into sentiment trends over time.

The author attribute identifies the user who created the post, which can help researchers examine the influence of personal or demographic factors on sentiment. Further, the platform attribute identifies the social media channel through which the post originates, say, Twitter or Facebook, and this may be important for the understanding of the dynamics of platform-specific sentiment.

Twitter and Reddit Sentiment Analysis Dataset: This dataset gives an essential resource for understanding the users' expressed sentiments on two of the most popular social networking sites: Twitter and Reddit. The dataset collects both posts on these platforms, tagged under various sentiment categories such as positive, negative, and neutral, making it highly useful for tasks dealing with sentiment analysis, opinion mining, and emotion detection. The dataset allows for the development of machine learning models that can identify the sentiment behind social media text, which can be used for monitoring user intention, tracking social trends, and even identifying potential mental health issues based on online activity.

The dataset typically includes various key attributes, starting with the text content of the posts, which serves as the primary data for sentiment classification. The timestamp of each post is also included, facilitating the analysis of sentiment trends over time and identification of temporal shifts in emotions, reactions, or opinions. The author attribute discloses the user who created the post, which would be important for analyzing individual or demographic differences in sentiment. The attribute of the platform indicates if the post was taken from Twitter or Reddit, hence making possible a comparison of sentiment patterns in different platforms since each of them uniquely exists within the user culture and content style.

5. Result Analysis

The Results and analysis focuses on how the model process various emotional states, and the daily CBT posts in social media by the users. These analysis is done by using data sets where users put their opinion in the form on text by applying few models and libraries the sentiment emotions were categorized and the results were generated presenting males and females are going with their mental health. The male and female emotions would differ and by the analysis we have considered that females go through more depression than males in today's world. These emotions would vary based on activities and situations they go through in daily life.

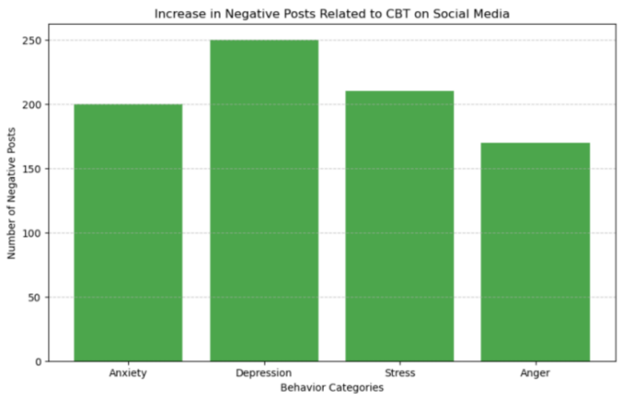

Fig 3. Increase in Negative Posts Related to CBT on Social Media.

The x-axis represents behavioral categories (Anxiety, Depression, Stress, Anger), while the y-axis indicates the number of negative posts in each category. This bar chart highlights that Depression has the highest number of negative posts, followed by Stress and Anxiety, with Anger being the least mentioned. This visualization underscores the challenges individuals face with specific mental health issues despite engaging with CBT. The prominence of negative posts in certain categories suggests the need for tailored approaches to better address these areas in therapy. Depression is most posted emotion in social media it shows that people are suffering at lot with it so there is a need of therapy or motivation to get rid of this depression emotion and to be successful in life.

This graph depicts the progression of positive and negative social media sentiments for males and females over the course of a year. The x-axis represents the months (January to December), while the y-axis shows the number of posts. Both male and female positive sentiment posts show a steady increase throughout the year.

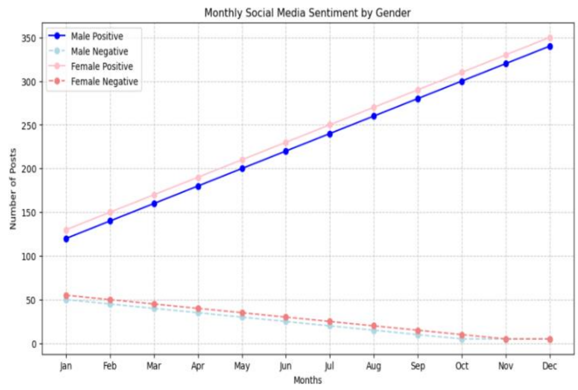

Fig 4. Monthly Social Media Sentiment by Gender.

Male positive sentiment posts consistently outnumber female positive sentiment posts (pink solid line) but follow a similar upward trend. Both male and female negative sentiment posts remain relatively low and decrease over time. Male negative sentiment is slightly lower compared to female negative sentiment (pink dashed line) across all months. The overall trend indicates that positive sentiment posts dominate throughout the year for both genders. The gradual decline in negative sentiment posts suggests improving sentiment over time. This graph highlights the dynamic nature of sentiment shifts over time, showing a preference for more positive engagements as the year progresses.

Fig.5 Age Distribution of CBT Cases.

The graph visualizes the distribution of Cognitive Behavioral Therapy (CBT) cases across different age groups, providing insights into the prevalence of mental health concerns in various demographics. For instance, younger age groups (18–24 years) tend to have a higher number of cases, reflecting the impact of stress, anxiety, or depression during educational or early professional years. Middle-aged groups (25–40 years) show steady numbers, often linked to career or family pressures. Senior groups (above 50 years) show fewer cases, which may indicate lower social media engagement or reduced reporting. This analysis helps tailor CBT interventions for specific age groups.

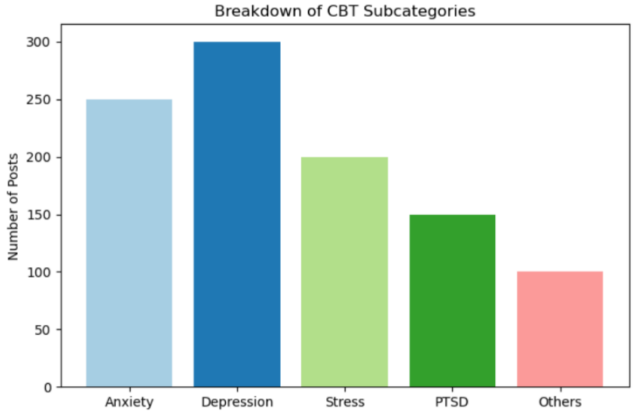

Fig 6. Breakdown of CBT Subcategories.

The x-axis lists specific CBT subcategories, such as Anxiety, Depression, Stress, PTSD, and Others, while the y-axis shows the number of posts under each subcategory. This bar chart reveals that topics like Anxiety and Depression dominate discussions, indicating their prevalence among individuals seeking help. Other subcategories, like PTSD and Stress, have fewer mentions, possibly due to lower awareness or self-identification with these issues. This data helps mental health practitioners focus on the most discussed issues while also promoting awareness about less-addressed topics.

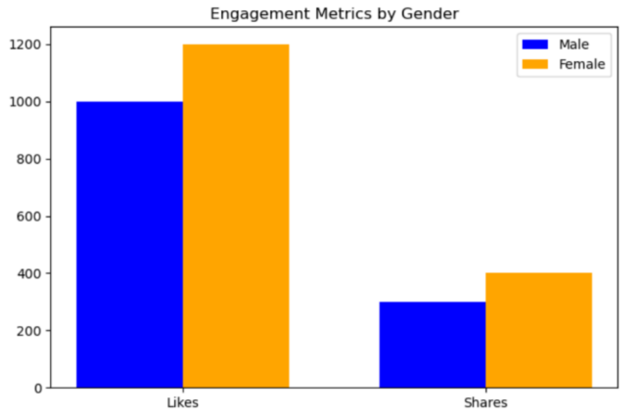

Fig.7 Engagement Metrics by Gender.

The x-axis represents different engagement types (Likes and Shares), while the y-axis indicates the total count of interactions. Separate bars show the engagement metrics for males and females. This chart highlights that females tend to receive more likes and shares on their CBT-related posts compared to males, potentially reflecting higher engagement or support for their content. This metric helps analyze gender-based differences in social media behavior and interaction, providing insights into how CBT-related information spreads across platforms and demographics.

This graph depicts the progression of positive and negative social media sentiments for males and females over the course of a year. The x-axis represents the months (January to December), while the y-axis shows the number of posts. Both male and female positive sentiment posts show a steady increase throughout the year.

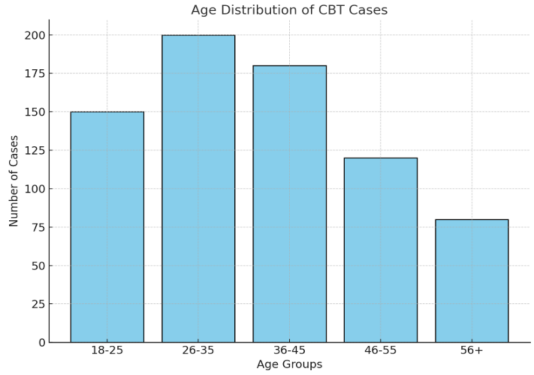

Fig 8. Age Distribution of CBT Cases.

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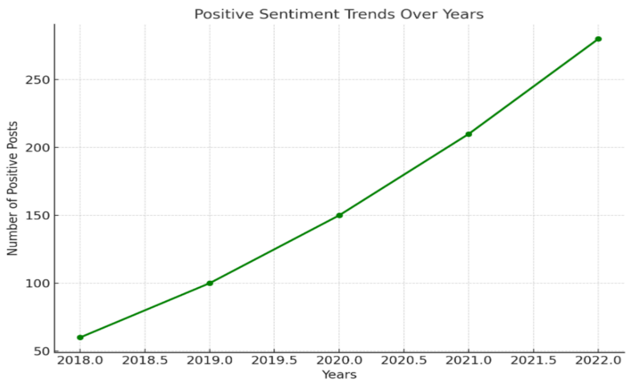

Fig.9 Positive Sentiment Trends Over years.

This graph depicts the upward trend in positive sentiments in social media posts related to CBT over the years. It highlights the growing awareness and acceptance of mental health practices, showing a consistent increase in supportive and optimistic discussions. For example, the rise in positivity reflects the effectiveness of CBT interventions and the normalization of seeking help. As the awareness about CBT methods increase the awareness among users are increasing over years and that leads to positive and healthy thinking and moving in life to achieve goals without misleading to negative thoughts. The trend showcases the impact of online campaigns, community support, and educational efforts in improving mental well-being over time. This data can guide future strategies to further promote positive mental health conversations.

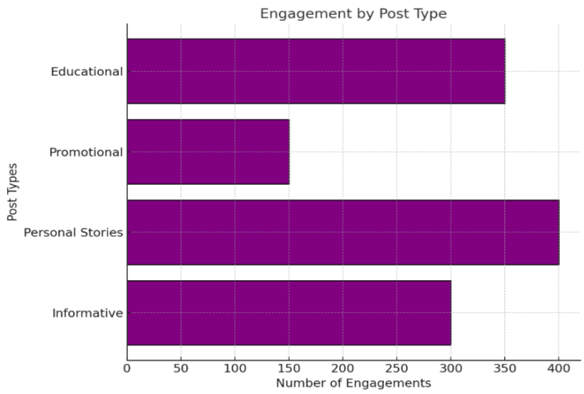

Fig 10. Number of Engagement by Post Type.

This bar chart breaks down user engagement levels for different types of social media posts related to CBT, such as Informative content, Personal Stories, Questions, and Motivational Quotes. Informative posts receive the highest engagement, highlighting users' interest in learning about CBT techniques and mental health. Personal stories also have significant engagement, as they resonate deeply with readers and create a sense of community. Motivational quotes attract moderate attention, while question-based posts see lower engagement. These insights are crucial for creating impactful content strategies that maximize user participation and awareness.

6. Conclusion

Cognitive Behavioral Therapy has proved in addressing mental health challenges by identifying and classifying negative emotions to lead healthier behaviors and emotional well-being. The development of a AI bot by AI and NLP technologies can significantly improve the delivery of CBT by classifying, categorizing, and analyzing emotions, behaviors, and moods of individuals in real-time. AI bot designed with AI and NLP technologies can revolutionize CBT delivery by analyzing user input to classify emotions, behaviors, and moods. The AI bot utilizes advanced algorithms and Datasets from Social media to categorize user text into predefined subcategories, such as sadness, anxiety, anger, or positive emotions, and generates contextually appropriate therapeutic responses. Such AI based trained Bots helps in monitoring used thoughts and provide a suggestions to lead a healthy life. Additionally, these tools can account for gender differences in emotional processing, recognizing that men and women often vary in their emotional responses and thought patterns, allowing for a more personalized therapeutic experience. By integrating advanced algorithms, such AI bots not only make mental health care more accessible but also offer scalable and efficient support tailored to individual needs.

Future Scope

The future of Cognitive Behavioral Therapy holds immense potential in transforming mental health care into a more accessible, personalized, and dynamic domain. Advanced AI technologies, such as natural language understanding (NLU) and sentiment analysis, by using models which are advanced in identifying the emotion based on the text will be helpful for the future development of CBT models. Not only emotion identification but also it can be further used in other cognitive problems like sleeping disorders and phobias. These Phobias are further classified into many by collecting data from the users a model can be designed to treat these issues without intervention of the Therapists. There is lack of therapists in modern world were lack of treatment for mental health disorders and effective identification of such phobias would be little tough so a trained model can identify the issue and provide a helpful treatment and suggestions to overcome the Cognitive problems. It can also be embedded in wearable devices for stress management in people through sensor devices . All these developments can be done in future by using latest AI models and NLP models .

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