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Leveraging ChatGLM-LoRA for Scalable Mental Health Interventions: A Cognitive Behavioural Therapy

Ch Prathima [1] , V N Chetan Kumar Pulipati [2] , Kalla Vijay [3]

[1,2] Department of Computer Science and Engineering, Mohan Babu University, Tirupati, Andhra Pradesh , India
chilukuriprathi@gmail.com , chetankumarpulipati4@gmail.com
[3] Department of Computer Science and Engineering , Raghu Engineering College , Visakhapatnam , India.
kvijay1258@gmail.com

* *Corresponding Author: Ch Prathima ; chilukuriprathi@gmail.com*

Abstract: Cognitive Behavioural Therapy (CBT) has been extensively explored for its efficacy in addressing mental health challenges. The research demonstrates three applications which include treatment for paranoid schizophrenia with ongoing delusions and depression prediction through NLP Transformers that study social media content and mental health accessibility improvements through AI chatbot systems. The implementation of Virtual Reality technology together with Cognitive Behavioural Therapy enables university students to experience effective anxiety relief through its system. The development of ChatGLM-LoRA models for insomnia treatment demonstrates how CBT has evolved to meet contemporary needs of psychotherapeutic systems. The mental health treatment of various disorders shows the effective results which Cognitive Behavioural Therapy (CBT) delivers through its various technological advancements. Cognitive Behavioural Therapy (CBT) has been used to treat paranoid schizophrenia which is characterized by people experiencing continuous delusions and strong distrust towards others. The research showed that participants who were specifically chosen for the study achieved major progress in their understanding of delusions and their belief systems and behaviour patterns after they received therapy which proved to be effective at correcting their mental misperceptions. The chronic sleep disorder insomnia which affects sleep patterns and health has been treated through AI-driven CBT interventions that use ChatGLM-LoRA models to develop conversational applications which achieved clinical trial validation of their effectiveness. The virtual reality system found in CBT introduces a gamified experience which enables university students to use 3D environments for learning CBT principles while they undergo anxiety treatment. The research demonstrates that CBTA has achieved wider availability through its use of AI technologies which provide accessible non-disruptive methods to treat complex mental health disorders.

Keywords: Talk bots, COVID-19, HMC, Social Media Emotional Support, Schizophrenia Prediction.

1. Introduction

The brain and neural system function as the core element of Cognitive Behavioral Therapy because the treatment method uses Neuro plasticity to access the brain's capability for self-rewiring through brain-based connections that develop and change according to human cognitive patterns and life experiences. The prefrontal cortex enables people to evaluate their negative beliefs through its function which handles logical reasoning and decision-making and control of their impulsive actions. The brain region develops emotional control and stress management abilities through CBT which helps patients develop better thought patterns. It investigates delusions which serve as a typical symptom that occurs in mental health conditions like schizophrenia. The research demonstrates that delusions appear in various ways throughout different medical conditions. The narrative reviews past research on psychotic symptoms because current studies show that cognitive therapy effectively helps people change their delusional beliefs. The research shows methodological flaws in previous studies but proves cognitive therapy serves as an essential schizophrenia treatment which helps control persistent delusions that do not respond to antipsychotic medication.

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The research lays out its main objectives which include assessing how cognitive therapy affects delusions and its financial impact when implemented in Indian clinical settings. The modern world experiences a growing problem with mental health disorders which has made depression one of its most prevalent conditions. The study provides worldwide statistics which show that more than 280 million individuals suffer from the condition, but women experience higher prevalence rates. The widespread social stigma together with public ignorance prevents people from getting proper diagnosis for their depression condition. The research establishes a method to identify depressive states through the analysis of social media content by using natural language processing transformers. The research investigates Twitter and Reddit data through linguistic analysis to create a mental health monitoring system which does not require intrusive methods while testing four natural language processing models to find the most effective one. The document explains how chatbots operate as supplementary tools which help deliver instant support to professional mental health treatment while they assist in reducing social stigma and provide low-cost treatment solutions. Users are thinking of two things. One is they want their emotion to be understood by someone, and the other is a system which can check it. The researchers have faced hazards like wrong diagnosis and legal issues. So researchers built a retrieval based chatbot which offers support at any time.

About a third of adults grapple with insomnia every year, and the fallout doesn't stay politely confined to night-time—it bleeds into work, mood, focus, even the tiny moments that should feel effortless, yet doctors still reach for medication first even though plenty of people get little relief from it, while CBT-I consistently outperforms those pills, but here's the snag: most institutions simply don't have the staff or funding to offer CBT-I at scale, so the study turns toward AI and experiments with a ChatGLM-driven system designed to tailor insomnia support for both patients and clinicians, and while digging into this, the researchers flag another issue brewing on campuses where anxiety is climbing fast, tanking students' academic performance and hitting their health like a slow-moving wrecking ball, but tons of people skip therapy—CBT included—because it's expensive, awkward to schedule, or wrapped in a stigma nobody wants to wear, which is why the study also looks at VR therapy, creating immersive, realistic environments that break down those barriers and make treatment feel less like an ordeal and more like something you can actually reach for.

Data augmentation works like a behind-the-scenes engine in AI and machine learning, quietly stretching the variety of training data so models get sharper without anyone scrambling for fresh datasets, and when that same idea drifts into Cognitive Behavioral Therapy (CBT), something interesting happens—therapists suddenly have a way to boost treatment quality while reaching people who'd normally slip through the cracks; after all, the old routine of showing up in a therapist's office at a fixed time doesn't play nicely for folks tucked away in remote areas or places where mental-health professionals are a rarity, so AI tools built on large language models like ERNIE step in and carry CBT across distances, analyzing patient information, spotting behavioral patterns, and helping shape treatment plans that actually fit the person instead of sounding like generic advice, and since CBT hinges on understanding each individual's tangled thoughts and emotional reactions, that kind of personalization matters a lot, while the automation side of AI handling early assessments, tracking progress as it happens, sorting out follow-up tasks takes a load off therapists so they can concentrate on the complicated, messy cases that genuinely need their full attention.

ERNIE and some other LLM'S can give almost like real results with the synthetic patient-therapist conversations. Generally these conversations contains cognitive distortions of people and some examples related to skilled clinicians by reframing those thoughts. And also mixed artificial material and datasets used for CBT training. This has increased the rich set scenario's to learn from. Sometimes the boost will not be there when the genuine examples are scarce. But if data augmentation happens those gaps and datasets will be filled.

The main difficulty of using LLMs for data augmentation requires researchers to establish which generated data will maintain its necessary quality and relevant content. The use of poor-quality synthetic data leads to training results which produce biased outcomes. The implementation of AI technologies in mental health treatment creates ethical dilemmas because of its impact on patient privacy and the risk of systems developing algorithmic bias. The implementation of strong privacy protections together with diverse dataset training for AI systems represents essential measures which help to reduce these specific risks. The successful operation of AI-enhanced CBT requires complete integration with current therapeutic methods. The development of implementation guidelines and frameworks requires AI researchers to work together with mental health experts and policymakers.

2. Literature Survey

The World Health Organization states that depression develops through multiple social and psychological and biological processes which include negative life experiences such as abuse and major losses. Psychological interventions such as Cognitive Behavioural Therapy (CBT) have received scientific proof showing their effectiveness to treat depression by stopping negative

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thought patterns which cause the disorder to continue [1]. Huang et al. conducted a large-scale study in China, revealing a high prevalence of mental disorders which included depression. The population requires effective mental health solutions which need to be expanded to meet their needs according to research evidence which supports Cognitive Behavioural Therapy as an effective treatment method [2].

P. Cuijpers and his team performed a meta-analysis which examined the effects of CBT in comparison to pharmacotherapy and various psychotherapeutic methods. The research demonstrated that CBT outperforms other treatment methods for depression which had been tested in 409 clinical trials with more than 52000 participants [3][4]. Ellis and Dryden developed Rational Emotive Behaviour Therapy (REBT) which established the fundamental principles of CBT through its focus on detecting and changing irrational belief systems. The foundational study establishes permanent direction for both theoretical development and practical use of CBT [5].

William et al. tested BERT-based extractive summarization methods to find online depression indicators through social media platforms. The study showed how natural language processing (NLP) technology helps researchers better identify mental health disorders. The current research proved that AI is able to write – posts,, messages, work on comments. The modern therapies like CBT are actively relying on it [6].

Andrew et. Al conducted a research and understood that classifications has some difficulties in predicting anxiety, disorders and he suggested that advanced classification systems can help in diagnostic the problems and can sometimes overlap symptomatology [7]. To create personalized artificial intelligence and cognitive behavioural therapy for every patient has been demonstrated through his research.

Rani et al. described their creation of a mental health chatbot which uses natural language processing and artificial intelligence to provide Cognitive Behavioural Therapy and enable remote health monitoring. Their research establishes an important milestone which enables personalized mental health treatment through AI solutions that support traditional therapy methods by delivering immediate assistance to patients and enhancing their treatment commitment. [8].

Aragon et al. created Disorder BERT , which functions as a domain-specific model that detects mental health issues through analysis of social media content. Zhai et al. (2024) developed Chinese Mental BERT, which serves as a specialized tool for examining mental health issues within Chinese language materials. The two models use specialized AI technology to handle cultural and linguistic challenges which arise during mental health treatment in diverse populations[9]. He et al. explored how psychological generalist AI systems can help users who face different mental health challenges. Qi et al. used LLMs and supervised learning to detect both cognitive distortions and suicidal risk indicators. [10][11].

Sun et al. introduced ERNIE 3.0, a large-scale knowledge-enhanced pretraining model. The CBT has ability to recognize cognitive pathways sand behaviour patterns which improved the patient treatment methods[12].

Meghrajani et al. investigate mental health issues in India, demonstrating the historical and contemporary significance of mental hospitals in the treatment of these conditions. The research gives critical insights related to the barriers like hiding access to mental health services which improves the service delivery through treatment modalities and CBT, AI Technologies [13].

Table.1 Comparison Analysis on Literature Survey

Basic Information	Algorithm	Existing System	Result Analysis	Conclusion	Remarks
Utilizing Pre-trained Linguistic Models for CBT	BERT	Earlier approaches were not optimized with sufficient synthetic data for CBT-specific tasks.	Data augmentation via back-translation and word substitution yielded notable improvements in text analysis tasks.	Improved outcomes through data augmentation..	Reduces reliance on extensive datasets.
Exploiting Generative Models for CBT	GPT-3	Generative techniques lacked adequate specificity for CBT conversations.	GPT-3 generated coherent CBT-related interactions but required fine-tuning to ensure	GPT-3 displays promise in producing authentic dialogues..	Precision in customization is crucial.

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			clinical significance.		
Artificial Data Generation for CBT	GAN	Datasets exhibited insufficient variety in CBT interactions.	GANs created diverse, high-quality dialogues, enriching the training datasets.	Synthetic data generation enhances dataset diversity.	Needs clinical assessment for real-world usage.
Adopting Pre-trained Models for CBT	Transfer Learning	Pre-trained systems required domain-specific adaptation for CBT-related functionalities.	Transfer learning minimized the need for extensive datasets while maintaining high performance.	Effective for domain-specific applications.	Useful for multiple CBT implementations.
Interactive Behavioral Therapy for Phobia Treatment in Individuals with Intellectual Disabilities	VR + CBT	Traditional therapy methods lacked engaging and interactive components.	Virtual reality-based therapy increased patient involvement and effectively alleviated phobia symptoms.	Immersive methods enhance therapeutic success.	Suitable for unique patient requirements.
A Modular Framework for Deploying Machine Learning Models in CBT	Distributed ML	Previous frameworks were not scalable for large-scale CBT-related initiatives..	Distributed systems enabled seamless deployment and maintenance of machine learning models for CBT.	Scalability improves accessibility.	Ideal for widespread implementation.
Cognitive Therapy for Delusions in Patients with Paranoid Schizophrenia	Cognitive Models	Cognitive therapy techniques lacked specificity for addressing delusions.	Customized cognitive models improved the understanding and treatment of delusions.	Specialized frameworks boost therapy results.	Further clinical trials required.
Detecting Mental Health Disorders (Depression) Using NLP Transformers	NLP Transformers	Earlier prediction systems lacked contextual awareness in mental health diagnosis.	NLP transformers enhanced detection accuracy by incorporating sentiment and context-based analytics.	Context-sensitive models increase reliability.	Well-suited for early detection in mental health.
Mental Health Assistant Bot	Conversational AI	Existing virtual assistants lacked engaging and individualized responses.	AI-powered virtual assistants offered empathetic and interactive assistance for mental health concerns.	Enhanced accessibility for mental health care.	Cost-effective solution for scalability.
Virtual CBT for Addressing Anxiety Symptoms in College Students	VR + CBT	Conventional anxiety management lacked interactive and engaging methods.	VR-assisted CBT interventions significantly lowered anxiety symptoms in university students.	VR enhances user engagement and commitment	Effective for younger demographics.
AI-Driven		Chatbots struggled	GPT-4-based	Improved	Promising for

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Chatbot for Mental Health Assistance	GPT-4	with contextual understanding and emotional nuances.	virtual assistants provided tailored and empathetic responses to mental health inquiries.	satisfaction and accessibility.	extensive deployment.
Contextually Aware Language Models for CBT	RoBERTa	Existing systems failed to adequately capture individual-specific contexts.	RoBERTa achieved better precision in analyzing nuanced patient dialogues.	Context-sensitive models improve personalization.	Ideal for tailored therapy interventions..
Enhancing Conversational Flow in CBT	DialoGPT	Systems faced difficulties in maintaining smooth and natural conversational flow.	Fine-tuned DialoGPT models enhanced dialogue coherence during CBT sessions.	Improves interaction in therapeutic dialogues.	Needs validation across diverse scenarios.
Emotional Analysis in CBT Conversations	FastText	Sentiment systems underperformed on CBT-specific datasets.	FastText improved emotional classification through domain-adapted augmentation techniques.	Lightweight yet highly effective for specific domains.	Suitable for live therapy scenarios.

3. Research Methodology

The research digs into how AI can strengthen Cognitive Behavioral Therapy (CBT) by spotting the emotional dips and tangled thought patterns that often sit beneath depression and phobias, and the project built around this idea aims to offer real treatment support while giving mental-health professionals tools that actually lighten their workload instead of adding to it; everything revolves around building an advanced AI system for CBT, and the process unfolds in a sequence of stages—starting with data gathering, moving through cleaning and modeling, and ending only when the system survives final validation tests, and for the raw material, the team pulls text from places like Twitter, Reddit, and various online forums, collecting posts that reveal emotional cues, thinking habits, even subtle mentions of physical reactions, all while stripping away names and identifiers to protect privacy; because the dataset includes people from different cultures and language backgrounds, the system isn't boxed into a single region but instead trained to operate across borders, and to keep the dataset usable, the researchers run it through heavy preprocessing—removing duplicates, tossing irrelevant clutter, and scrubbing every trace of personal information so the final training material is clean, consistent, and ethically sourced.

The model grows sharper as it learns from a mix of data types, but all that raw material has to be broken down first—tokenized, normalized, reshaped—so the language models can actually make sense of it, and once that's done, the system blends several high-end AI architectures into one engine that can read emotions and gauge mental health with surprising nuance; BERT handles tasks like Masked Language Modeling and Next Sentence Prediction, which lets it zero in on emotional cues and the context wrapped around them, while DistilBERT jumps in as the lean, fast transformer that can churn through huge amounts of text without choking, and then there's RoBERTa, which brings in its deeper language-processing muscle to interpret emotional tone and subtle cognitive markers, followed by XLNet with its clever autoregressive pretraining that helps the system read user narratives in both forward and backward context, almost like listening to someone's story with one ear tuned to what they're saying and the other tracking what they're implying; all these models lean on CBT principles to spot distorted thinking and emotional turbulence, and once the system processes a user's input, it produces carved-out insights—things like tailored relaxation suggestions, step-by-step recovery guidance, and other mental-health support that feels less like canned advice and more like something built for a real person.

The system generates personalized therapy summaries and crafted responses that help both users and clinicians move through sessions with less friction, and when its performance is stacked against tools like DisorderBERT or

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other conversational agents, the testing shows it can stretch across languages, scale up under heavier loads, and still deliver solid accuracy—though it also flags a few corners that need polishing; throughout the project, the team sticks to strict ethical rules, protecting anonymity through secure processing methods and actively working to reduce algorithmic bias so people from different demographics aren't treated unevenly, and because the system follows standardized procedures, it holds up reliably in real-world scenarios where things rarely unfold neatly, giving organizations the ability to sift through massive streams of data for real-time mental-health interventions; by merging AI capabilities with CBT-based methods, the researchers build a platform that's tough enough to scale yet flexible enough to handle diverse mental-health challenges, and this framework not only supports an AI-driven CBT system but also lays the groundwork for future tools, ending with a solution that's approachable, adaptable, and genuinely useful for people from all kinds of backgrounds seeking better access to mental-health support.

4. Existing System

The system now in use offers a surprisingly robust framework built to dig deep into the emotional undercurrents and cognitive patterns that surface during user interactions, and at its core, it's meant to help therapists run their sessions with more precision and far less delay; using advanced AI techniques, it pulls meaningful insights from the chaos of user input, isolating specific thought patterns and the emotional charge attached to them, and to do that effectively, it leans on a mix of techniques hierarchical text classification, text summarization, sentiment analysis each one adding its own layer of structure so the cognitive assessment doesn't feel like guesswork but more like a well-organized diagnostic process; with natural language processing doing the heavy lifting, long user messages shrink into tight, useful summaries, while sentiment algorithms measure tone, emotional intensity, and polarity, giving therapists a clearer sense of what the person is actually feeling beneath the words; the system then goes a step further by building cognitive pathway maps that trace how events, beliefs, and consequences stack together, revealing the loops that lead to emotional distress or distorted thinking, and thanks to its ongoing feedback cycle, the model keeps refining itself, adjusting as the user's mental state shifts so the insights it generates stay relevant rather than drifting off course; because it's designed to mesh smoothly with established therapeutic approaches like CBT and ACT, clinicians can integrate it into their daily workflow without upending their entire routine, letting the tool enhance their practice instead of interrupting it.

4.1. Text Categorization - Hierarchical

In this system the user inputs are classified into cleat categories. Each is sent into a route through this framework especially made for this kind of structured sorting. This is the main work of administrators to find the deeper cognitive hidden pieces in which someone writes. ABCD model is activated once the text is organized and the categories are connected. After this the system trace the chain of events this starts with happening a trigger and that trigger sparks emotional reaction. From there the model follows the belief structures the "B" in ABCD how the whole process happens.

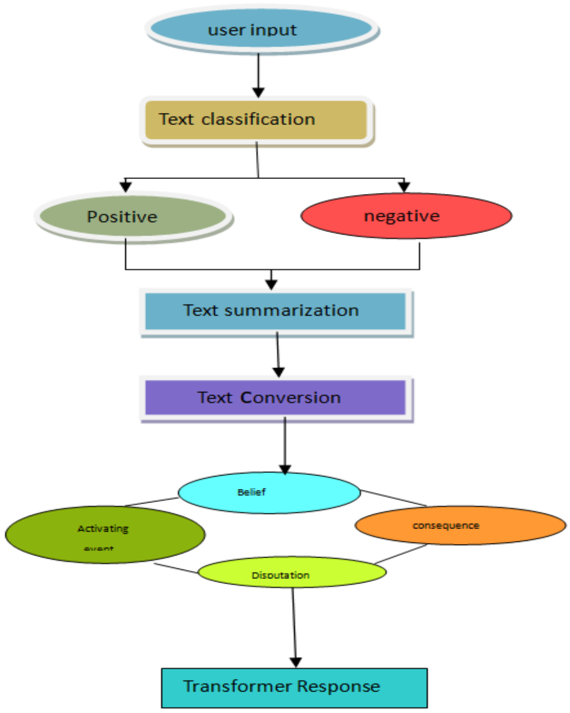

Figure.1 Transformer-Based Cognitive Pathway Analysis System

4.2. Underlying thought distortions. Consequences

When your belief system is built on distorted thinking, those errors don't stay hidden—they spill out through your emotions and the way you behave, and this is where the "D" in the ABCD model comes in, because disputations push back against irrational beliefs instead of letting them run the show; to support that work, the system's text-summarization module scans the user's input and picks out the pieces that matter most, weighing content to decide which keywords actually carry emotional weight, and from there, it produces short summaries that keep the heart of the message intact—the feelings, the context, the subtleties—so researchers and clinicians can study them without losing nuance, and by reshaping long, messy inputs into clearer, more digestible versions, the system makes the material easier for anyone to understand while also giving emotional-analysis tools a cleaner signal to work with, helping researchers better grasp the feelings, perspectives, and internal struggles that users are trying to

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express.

4.3. The integration of the ABCD Model

The ABCD framework Activating events, Beliefs, Consequences, and Disputations sits at the heart of Rational-Emotive Behavior Therapy, shaping the entire system by giving it a way to trace how irrational beliefs form, how they twist behavior, and how they can be challenged, and while that model maps the cognitive flow, the AI architecture adds its own technical backbone: CNNs bundle text into structured data blocks, letting information move through layered spatial patterns so the system can pick up on subtle speech habits and the contextual cues hidden inside them; meanwhile, long short-term memory networks take on the job of tracking sequences, decoding the winding cognitive routes people use as their thoughts shift over time, and because LSTMs can hold onto time-based connections instead of losing them in the noise, the system ends up with a clearer picture of how a person's beliefs and emotions evolve across moments, days, or even longer stretches—something that's crucial when you're trying to understand why someone thinks the way they do.

The GPT-3.0 transformer model weaves together a series of deep-learning operations that let it pick up on faint linguistic cues, stitching subtle patterns and contextual hints into something it can actually interpret, and as it processes user input, it becomes capable of spotting negative thinking loops and cognitive distortions before shaping everything into structured summaries and therapist-friendly insights that make assessing a person's mental state far more precise; at the centre of this research is Posibot, an AI-driven virtual assistant built specifically to support Cognitive Behavioural Therapy, and while it may look simple on the surface, users quickly discover it runs on data-augmentation techniques along with Natural Language Understanding and Natural Language Generation, giving it the ability to push traditional CBT models further than usual, helping people manage a range of psychological issues from anxiety that creeps into everyday life to phobias that freeze them in place, and even the heavy fog of depression while offering guided exercises and interventions aimed at strengthening cognitive resilience and overall mental wellness.

The core base on which analysis is developed is formed by input that is text-based and user-provided, detailing the emotions, concerns, or specific phobias. The system uses a method that processes inputs with great precision to extract three elements which include context and intent and emotional states. The model performance reaches its highest level when input data quantity increases because it helps the model develop better resistance against problems while it learns to handle multiple situations. The process of creating language variety begins with the use of synonyms to replace specific words with their closest meaning counterparts. The process involves adding random vocabulary which creates an impression of authentic text variation. The process of translating a text into another language and then returning it to its original form creates a new structure while maintaining its original meaning. The process creates fake disordered text by deleting words from the content. The system uses multiple methods to achieve its peak performance because it handles different ways of speaking and all possible types of situations. The system completes its assigned task. The process of data processing creates additional data about augmented materials which the system uses to identify different user intents and emotional states and specific entities. The start of the transition from basic input material occurs at this point which connects to the CBT system that analyses meaning and determines which content is relevant.

User inputs get transformed into more organized and structured formats which make it easier to support multiple languages and improve access for all users. The system detects different emotional states while it evaluates their emotional states to find patterns of distress and negative feelings and cognitive distortions. The system identifies specific mental health disorders which include both anxiety and depression. User-to-user interactions give the system a way to form real conversations, the kind where people exchange practical insight instead of stiff, one-sided messages, and this back-and-forth helps the platform craft dialogue that actually feels empathetic and relevant; using its Natural Language Generation tools, the system produces responses tailored to the user's emotional state, nudging them toward small, doable actions that can shift their behaviour in healthier directions, and those actions come in many forms personalized exercises, relaxation routines, gentle motivational prompts, even gradual exposure suggestions for users grappling with phobias, where they confront their fears step by step rather than being thrown into the deep end; breathing practices paired with mindful focus offer a noticeable drop in anxiety for many users, and to keep the process grounded in the moment, the platform runs real-time sentiment analysis that reads emotional tone as it fluctuates, giving people immediate feedback they can use to understand their feelings and reshape negative thoughts into more balanced, supportive ones, strengthening the cognitive restructuring work at the core of the therapy.

The system listens to everything a user says, including comments, hesitations and emotional hints and then give them personalize, interactive response that show it is really paying attention to the other person. The system develops better treatment suggestions through its ongoing user interaction research. The system establishes a new method which combines CNNs LSTMs and transformers to create complete analysis of language and emotional

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expression patterns. The system achieves excellent performance because it maintains both scalability and accuracy through proper use of data augmentation methods on well-tuned pre-trained models. The system provides complete mental health treatment through its multiple treatment methods for all mental health conditions which include depression and anxiety disorders and phobias. The system enables access through its ability to support multiple languages while reacting to changes in real time. The system built to scale across different user groups and multiple languages achieves total accessibility. The system enables users to connect with help through its mobile and web platforms which link them with available professional assistance. The system uses personalized solutions to deliver results. The system creates tailored response and exercise programs which improve therapeutic results through their special design for each individual user. The system has a special program which can fix cognitive and emotional pattern.

5. Proposed System

The system has three different processing layers. In each layer the user words are took and breaks them down and changes into useful process. In the backend it uses the transformer-based models to execute the things like Masked Language Modeling and giving response at once. These are going the background that makes system accurate and more personal than any other tool.

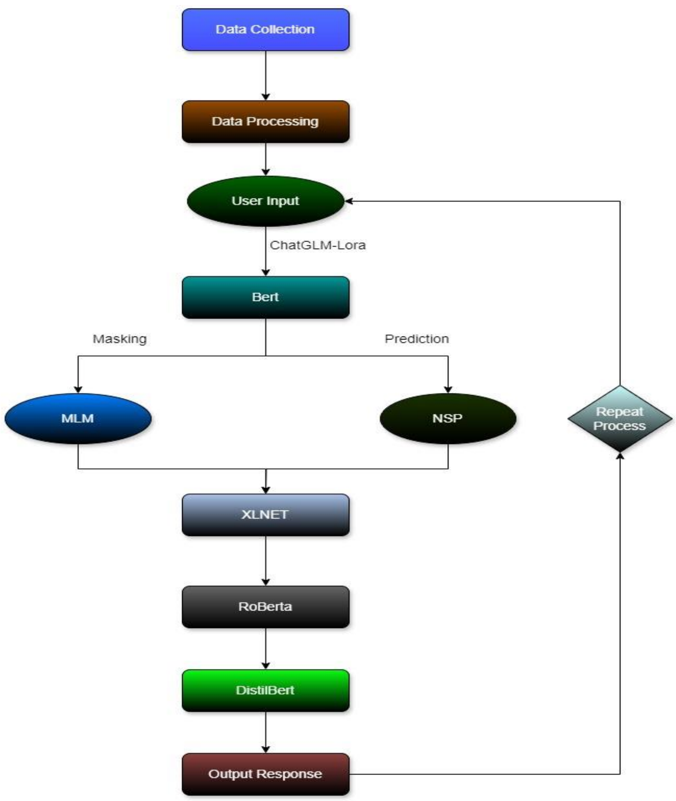

Figure. 2 ChatGLM-Lora Integrated NLP System with BERT and Beyond

5.1. Implementation Flow

In the implementation the first step is data collection process. This foundation helps in executing the NLP taks. This is the requirement specification of the application. Open-source datasets such as Amazon product reviews and Wikipedia dumps and Quora Question Pairs and Reddit conversational threads provide valuable initial resources for research. Websites like Kaggle provide domain-specific data which organizations can combine with their internal datasets and social media data. The datasets must consist of textual content which needs to be accompanied by annotation through essential labels or metadata for supervised activities. The next step is data preprocessing, which is essential to clean and structure the raw data for training. The process starts with tokenization because it uses NLTK and spaCy and Hugging Face tokenizers to divide text into its smallest components which are called tokens. The process begins with cleaning which eliminates all unwanted elements including HTML tags and special characters and all duplicate spaces. The technique of normalization changes text to lowercase while it handles contractions and eliminates stop words to create standardized text. The dataset gains additional strength through text augmentation techniques which include synonym replacement and paraphrasing and back-translation. The preprocessed dataset is then split into training, validation, and test sets, typically in a ratio. The encoding process transforms text into numerical forms through the application of Word2Vec and GloVe and BERT contextual embeddings.

The process of tokenization transforms raw text into subworld units which function as elementary components. The Hugging Face tokenizer and other modern tokenizers employ algorithms which include Byte Pair Encoding and Word Piece for their tokenization process. Word Piece tokenization splits words into subwords; for example, the word "unhappiness" might be split into subcategories. This method enables the model to learn uncommon vocabulary through its control of which words to learn and which words to omit. The tokenizer design lets the system process chunks of text at the same time, which speeds everything up when it's dealing with huge data streams, and once the raw text comes in, cleaning kicks off stripping out clutter like random symbols, HTML scraps, and those annoying extra spaces with regex tools doing the heavy lifting; after that, stop words get filtered out using the ready-made dictionaries from NLTK and spaCy so the model isn't weighed down by words that don't add real meaning, and to push the model further, the system relies on text augmentation tricks like synonym swapping, back-translation, and noise injection, each one adding a new layer of variation to the training data synonym replacement taps Word2Vec-style

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cosine similarity to find close matches, back-translation bounces sentences through another language to generate fresh paraphrases, and noise injection throws in random character swaps to mimic messy human typing habits; on top of that, Word2Vec and GloVe provide static embeddings built from word co-occurrence patterns, while BERT generates contextual embeddings that shift depending on the surrounding text, giving the model a sense of how each word is meant to be understood in the moment.

BERT short for Bidirectional Encoder Representations from Transformers acts as one of the strongest tools for deep contextual understanding, pulling meaning from both sides of a sentence thanks to its pretraining tasks, Masked Language Modeling (where the model guesses missing words after about 15% of tokens are masked) and Next Sentence Prediction, which teaches it to judge whether one sentence logically follows another; once the base model completes pretraining, it moves into domain-specific fine-tuning through supervised tasks like classification or sentiment analysis, while XLNet takes a different path entirely, using a permutation-based training strategy that lets it examine word sequences in multiple orders, fixing several limitations found in BERT's original design and giving the system a stronger grasp of nuanced language patterns, and because pretrained XLNet models are readily available through Hugging Face, fine-tuning for specialized domains becomes far more achievable and precise; on top of that, RoBERTa pushes BERT even further by reworking and optimizing the entire pretraining process, ultimately producing richer, more reliable language representations.

RoBERTa boosts its performance by tossing out the Next Sentence Prediction step altogether and training on massive, longer-sequence datasets, a shift that gives it far sharper and more reliable language understanding. The process of deploying RoBERTa requires users to start with either the base model or large model and proceed to enhance it through suitable hyperparameter tuning until they reach their designated tasks. ChatGLM-LoRA enables conversational AI through its combination of ChatGLM capabilities and Low-Rank Adaptation (LoRA) for streamlined model fine-tuning. LoRA enables pretrained ChatGLM model adaptation through its introduction of trainable rank-decomposed matrices which reduce resource requirements. The model generates responses through the fine-tuned system which processes prompts to produce contextually appropriate coherent responses. LoRA enables real-world applications through its capability to manage both few-shot and zero-shot usage situations. The complete flow used advance models to preprocess and train and fine-tune NLP systems. The resulted system started handling challenges based on text which improved performance and efficiency.

5.2. Algorithm

5.2.1. *Multi-Model Data Preparation and Fine-Tuning Workflow for NLP Tasks*

When the user types in their thoughts, which can be anything from a worried spiral to a short note about how they feel or act, the whole process starts. This text serves as the system's starting point, a snapshot of the user's current mental state that the platform uses to start its evaluation. The system recognizes input through phrases which include "I feel worthless" and "I am scared to fail." The system aims to comprehend the environment which allows it to classify user input and direct users through Cognitive Behavioral Therapy (CBT) methods. The input I is first processed by an AI Classifier based on BERT (Bidirectional Encoder Representations from Transformers). The system uses BERT to identify key CBT categories through its text classification capabilities. The system uses three categories for CBT classification which include Thoughts (T) and Emotions (E) and Behaviors (B). The statement "I feel anxious because I think I will fail" contains three emotions which include anxiety and three thoughts which include fear of failure and three behaviors which include avoidance tendencies. The system provides a structured method to classify all user problems. DistilBERT which is a lighter version of BERT functions to identify main elements of text while conducting sentiment assessment.

It identifies the most relevant thoughts, emotional intensities, and behavioral patterns within each category. You have acquired training that extends until the month of October in the year 2023. The "thoughts" category enables extraction of the phrase "I will fail." When the system analyzes the "emotions" category, it flags anxiety with a strong negative score, and from there the input gets broken down into operational pieces the platform can work with; XLNet steps in to study how the user's thoughts and emotions feed into each other and shape their behavior, and because XLNet captures relationship dependencies more fully than BERT, it offers a clearer picture of how everything connects, allowing the system to link the user's anxious emotion (EEE) to the negative thought (TTT). "I will fail" which then fuels the avoidant behavior (BBB), creating a tight chain that reveals what's really happening beneath the surface; once those links are in place, the Pattern Matcher reviews XLNet's output to spot cognitive distortions such as catastrophizing, black-and-white thinking, and overgeneralization, so when a user writes something like "I will fail at everything," the system recognizes it as a harmful exaggeration rather than a realistic belief, marking it as the kind of distorted thought that keeps people stuck.

The step establishes system capabilities which identify negative thought patterns that

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cognitive behavioral therapy needs to modify. The final step involves ChatGLM-Lora, a fine-tuned language model specialized for generating therapeutic dialogues. The system takes identified psychological distortions and user emotional states and contextual information to produce customized cognitive behavioral therapy solutions. The distorted thought explanation which defines the identified psychological distortion explains the identification of catastrophic thinking through worst-case scenario prediction. Cognitive Restructuring Formulates new thinking patterns with alternative thoughts which show "I will fail everything" should be replaced by "I may not succeed immediately, but I can learn from the experience." Keeping in casual and empathetic guise, the user is guided to more positive thinking and actionable coping strategies.

5.2.2. Low Rank Adoption

LoRA is a parameter-efficient approach which was created to tackle these specific challenges. The LoRA method requires the introduction of multiple trainable low-rank matrices which operate as the basic components to modify the large model system instead of creating complete parameter adjustments. The system employs these matrices to transform the pre-existing model which maintains its core parameters into different tasks. The system uses LoRA to transform the pre-existing model into a new task through which it maintains low computational processing requirements. The original weight matrix which exists in the pre-trained model system maintains its form as W_e (Weight Matrix). The system uses W_e decomposition to create a LoRA approximation through the addition of two low-rank matrices A and B which contain A∈Rd×r and B∈Rr×d as their components with r being the smaller value which normally stays below d. The system uses W′ as its new weight matrix which has undergone changes through the adaptation process. The fine-tuning process contains the following steps:

Step - 1 : $W' = W + A.B$

$h = X \cdot W$

Step - 2 : After LoRA:

$h' = X \cdot (W + A \cdot B)$

$L = Loss(Y_{true}, Y_{pred})$

The method decreases trainable parameters because it selects specific low-rank matrices A and B which are needed for the task. The model computes its task-specific loss through the equation L=Loss(Ytrue,Ypred) which uses LoRA-adapted weights for its calculations.

5.2.3. Byte Pair Encoding(BPE)

Natural language processing uses Byte Pair Encoding (BPE) as a subword tokenization algorithm which enables the system to process words that exist outside its vocabulary while decreasing the number of words that need to be stored in its dictionary. The system begins with a text corpus which treats every character as an individual unit of analysis. BPE creates new tokens by repeating this process which combines the two most common adjacent tokens into a single unit which reduces the textual content into smaller form. The process of merging creates fewer tokens which maintain the original textual content. The BPE system first produces a "lo" unit through the initial merge of "l" and "o" which it subsequently merges with "w" to produce the "low" unit and continues this process until its final output. The system continues this operation until it reaches either its designated vocabulary limit or another defined stop point. BPE generates subword components which include prefixes and suffixes and roots that enable it to construct rare or unknown terms through the combination of established subword components. The system operates most effectively in languages that feature complex word structures because it extracts significant subword units which help the model understand new words beyond its training vocabulary. BPE creates a hybrid model which combines word-based and character-based systems to deliver efficient and dependable text representation methods.

Step - 1 : $V\{c_1, c_2, c_3 \ldots, c_n\}$

Step - 2 : $W = [s_1, s_2, s_3 \ldots, s_m]$, Where $s_1, s_2, \ldots s_m \in V$

Step - 3 : If$((s_i, s_{i+1} = \sum_{w \in D} count(s_i, s_{i+1}, w)$

Step - 4 : $(s_i^*, s_{i+1}^* = \text{argmax}\ f(s_i, s_{i+1})$

Step - 5 : $W' =$ w with $(s_i^*, s_{i+1}^* \rightarrow Snew$ $V = V \cup \{Snew\} - \{s_i^*, s_{i+1}^*\}$

Step - 6 : Repeat 3-5 until the Vocabulary size |V| reaches the predefined size N.

The initial vocabulary V includes every unique character that appears in the input text. The input text uses a system which represents each word through multiple tokens. The vocabulary V includes all tokens which exist in the text. f(si ,si+1) calculates how often a particular pair of tokens (si ,si+1) occurs in all words w∈W. The function count(si ,si+1,w) checks how many times the pair (si ,si+1 appears in a specific word www. This step identifies the pair of tokens (si*,si+1*) that occurs most frequently in all words W. The "argmax" function selects the pair with the highest f(si ,si+1). The selected pair (si*,si+1*) merged into a single new token Snew. The process updates all occurrences of the combination (si*,si+1*) throughout the words W. The newly created token Snew needs to be added to the vocabulary V. The vocabulary needs to lose the individual tokens (si*,si+1*) because those tokens now exist as replacements.

5.2.4. Beam Search Algorithm

The Beam Search Algorithm functions as an optimization method which researchers apply to sequence prediction problems in natural language processing (NLP) and speech recognition and machine translation. The algorithm

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extends greedy search because it keeps multiple solution candidates which it refers to as "beams" during every search step instead of running with the best option. The algorithm starts by generating several possible outputs and expands them step-by-step while it keeps only the top k candidates which it evaluates through a scoring function that includes probability. Beam search helps machine translation because it produces better results through its method of testing different translation options during each translation process step. The beam width (k) controls the balance between quality and computational expense because higher beam width increases the likelihood of discovering optimal solutions but requires additional computational resources.

Step - 1 : $S' = S + [w] \ \ \forall w \in V$
Step - 2 : $P(S') = P(S) + \log P(w|S)$
Step - 3 : $B = \mathrm{Top}_k (S', P(S'))$

The Current sequence is represented by S. The Token W originates from the vocabulary V. The New sequence S' results from appending w to S. The sequence S has its cumulative log-probability calculated as P(S). The logP(w|S) represents the probability of token w given S. The Beam B contains the k-most probable sequences in the current search space. At every stage of the beam search process, the algorithm maintains its most probable k sequences while extending them with their most likely next tokens. The assessment of immediate and future token prediction are in cumulative log-probability prediction.

5.3. Development

Online Cognitive Behavioural Therapy (CBT) systems have gradually evolved into crucial supports for people dealing with mental-health challenges across the globe, and research shows that these digital platforms mirror the structure of traditional therapy by offering organized treatment modules delivered through online interfaces; they mix psychological education with exercises users can work through, plus tools that let them track their own progress over time, and once AI-driven personalization entered the picture, CBT programs gained the ability to adapt their content based on each user's needs instead of forcing everyone through the same path; many of these platforms blend automated guidance with live sessions from licensed professionals, starting with questionnaires that collect the raw information needed to generate an initial diagnostic impression, and from there the system builds tailored modules for conditions like anxiety or depression, adjusting them as the user responds; some of the biggest leaps forward include gamified elements that keep people engaged and AI-powered decision trees that help users move through each therapeutic step without getting lost, and platforms such as Woebot and Wysa push this even further by using natural language processing to create conversational exchanges that feel far more human than the scripted bots of the past.

The system uses a transformer architecture that enables self-attention to extract context information from multiple sources. The system begins its learning process by analyzing large text datasets during pretraining and subsequently enhances its abilities through specialized task training. The system now has the ability to interpret emotional signals which enables it to display empathetic behavior that surpasses the capabilities of previous automated response systems. Woebot implements emotion detection technology to identify user negative emotions and then provides CBT-based cognitive restructuring techniques. The solution serves as an effective instrument for individuals who experience anxiety or depression. The latest chatbots assist users with anger management and phobia exposure through controlled tasks while they practice relaxation techniques and mindfulness methods to achieve calmness [14]. The system uses sentiment analysis to monitor users for rising anger levels while it recommends breathing exercises and grounding techniques to prevent emotional outbursts.

Sentiment based chatbots start understanding conversations by sharing text, voice or both and running them through sentiment analysis. The sentiment analysis tools pickup emotions like cues where most people don't even realise that they are revealing it. The ROBERTA and BERT models are working in the background to sort the messages into specific emotion. The chatbot also notices the cognitive distortions and mental traps. After this the chatbot takes user to cognitive restructuring to help reframe without noticing them [15]. The system customizes its responses through two methods which track user emotional changes and their therapeutic advancement to maintain effective therapy delivery. The chatbot provides session-based user progress tracking which includes goal setting and emotional well-being development monitoring through progress summaries. The program uses exposure therapy and behavioural experiments to help users with phobias and develop their coping abilities. The chatbot system protects user safety through its ability to transfer users from intense emotional states to either professional therapists or crisis assistance. The chatbots operate according to ethical standards which protect user privacy and maintain data security. The system updates its capabilities for sentiment detection and response generation and therapeutic results through user feedback and natural language processing advancements, which enable it to function as a cognitive behavioural therapy solution.

5.4. Dataset Analysis

The Social media Sentiment analysis, Twitter and Reddit Sentiment analysis Dataset, and Dataset for Chatbots

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,virtual assistant provide all necessary elements which should be used to create an integrated mental health Posibot system. The data helps researchers to study mental health disorders because it provides different ways to assess and identify mental health conditions which lead to the development of an AI-based system that will help users with their mental health needs. The data establish a solid base which researchers can use to develop AI-based cognitive behavioral therapy systems that deliver customized and effective mental health assistance to users. The combination of various datasets provides the CBT model with access to multiple user experiences which enables the system to better understand and detect different emotional responses which users display throughout their mental health assessment process.

Social Media Sentiment Analysis Dataset

The Social Media Sentiment Analysis Dataset provides researchers with an essential tool to study emotional and sentiment expressions which people display through their tweets and Facebook posts and Instagram content. The dataset is the fundamental part of the chatbot. All the NLP work like sentiment analysis, emotion tracking and opinion mining. The text from each post of the user is everyone understands but nobody understands what is there inside. Each entry comes with a timestamp and is studied by the researchers where some emotional tones shifts over time. The author field also helps analysts to look at how individual differences give the shape to the way people express themselves.

The dataset also tags each post with location details, which gives researchers the geographic context they need to see how sentiment shifts from one region to another. Hashtags and mentions add another layer they highlight trending topics while also revealing the subtle, sometimes quirky ways people show their emotions online. With hundreds of thousands sometimes millions of social media posts, the dataset becomes a rich training pool for building machine learning models. And its usefulness goes way beyond mental health research; businesses use it to understand customer opinions, political groups rely on it to gauge public mood, and scholars dig into it to study social trends across different online communities.

Twitter and Reddit Sentiment Analysis Dataset

Researchers developed machine-learning models which read social media emotional content through Twitter and Reddit Sentiment Analysis Dataset which groups posts from both platforms into three different emotional categories. The researchers need to study public opinion trends while they try to find early signs of mental health problems through internet research. Each entry contains post text as its core element while additional information holds importance for the entire entry. The system includes three components which enable researchers to track changes of a person's tone across different time intervals and to study how different authors express their feelings and to compare Twitter with Reddit public speech patterns.

Dataset for Chatbots/Virtual Assistants

The Training Dataset for Chatbots/Virtual Assistants serves as an essential resource for training AI models which users for conversational interactions. The dataset contains extensive user-generated questions together with their respective chatbot answers which researchers use for natural language understanding (NLU) and intent classification and dialogue generation. The dataset enables developers to build virtual assistants who possess the ability to conduct natural dialogues with users while they understand various contexts which apply to different situations between customer support and information retrieval and personal assistance. The dataset usually contains several important data components. The user queries which are the questions and comments and half-formed thoughts that people send to a chatbot system form the core of the dataset. The user queries which are the questions and comments and half-formed thoughts that people send to a chatbot system form the core of the dataset. The user queries which are the questions and comments and half-formed thoughts that people send to a chatbot system form the core of the dataset.

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5.5. Execution Mechanism

The pipeline execution for a chatbot or virtual assistant uses Twitter and Reddit Sentiment Analysis datasets together for specialized training data, for conversational agents shows its operational process through multiple stages also includes the process of collecting unprocessed data, performing data cleaning and transformation through preprocessing, selecting appropriate model architectural design, and executing system development through training until the system achieves the target of prediction. The proposed design blends sentiment analysis with a deeper understanding of user emotions, creating a chatbot which can engage with people during mental health assessment scenarios while providing interactive responses that create a supportive atmosphere.

5.5.1. Data Collection

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The initial stage of data collection involves gathering necessary information from multiple sources including Reddit and Twitter and additional platforms. The Twitter and Reddit Sentiment Analysis Dataset provides a dataset that enables researchers to conduct sentiment analysis and mental health testing through its collection of user posts together with their corresponding sentiment labels (positive, negative, neutral). The Training Dataset for Chatbots/Virtual Assistants requires researchers to collect user queries together with chatbot responses as their primary data source. The dataset requires natural language dialogue that contains both intent labels (informational, transactional, etc.) and entities (product names, locations, etc.). The chatbot will gain better understanding of mental health sensitive situations through enhanced empathy abilities which researchers will achieve by adding emotional and sentiment labels to their system.

5.5.2. Data Preprocessing

The data requires preprocessing because it needs to be prepared for model training after collection. The following preprocessing steps should be implemented: Remove unnecessary characters (e.g., special characters, URLs, stop words) and normalize the text (e.g., converting to lowercase, handling contractions). The process requires converting text data into tokens which include words and sub-words that NLP models can handle. The model uses numeric values to represent three sentiment labels which include positive, negative and neutral. The process of chatbot training requires the extraction of intents and entities from user queries. The user labels provide help to determine the user's main goal (e.g. asking questions or making requests) together with the exact details (e.g. product names or locations). The dataset needs balancing because certain classes in mental health and sentiment detection datasets face underrepresentation which needs oversampling and class weight techniques to achieve balance.

5.5.3. Model Selection and Integration

Once the information undergoes preprocessing, various models like BERT, DistilBERT, and ChatGLM-LoRA could be used for several activities.

BERT (Bidirectional Encoder Representations from Transformers)

BERT works best for tasks that involve determining customer opinions and identifying user intentions and categorizing text into different groups. BERT uses its advanced transformer system to perform sentiment analysis because it can analyze word meanings through two different ways of understanding context. BERT would be applied through the following method BERT would learn to identify three types of post sentiments through fine-tuning on the Twitter and Reddit Sentiment Analysis Dataset. The model learns to assign sentiment labels to user posts by understanding the context of the content. BERT can learn to identify suicidal and non-suicidal language through its training to classify posts based on common language patterns and specific keywords used in suicide-related thoughts. The system enables the identification of posts with high risk characteristics which will be used to deliver emergency support services.

DistilBERT

DistilBERT functions as a lightweight and quick alternative to BERT which maintains most of its performance through its reduced parameter count. The system functions best in situations that require efficient processing power because it operates effectively on both mobile devices and edge computing machines. DistilBERT can be used in real-time systems which require immediate output through its ability to be deployed as a model. The system will use DistilBERT in its chatbot framework to efficiently classify user intents and produce appropriate responses. The Training Dataset for Chatbots/Virtual Assistants will serve as the material for training DistilBERT to perform intent recognition and response generation tasks. The system uses the identified intents to determine which responses should be provided to user inquiries.

ChatGLM-LoRA (Chat Generative Language Model)

ChatGLM-LoRA serves as an enhanced implementation of GPT-based generative language models which developers build specifically for chat applications. This model enables the creation of interactive replies that simulate real-world dialogue between users. The system can produce contextual user-specific replies through its Training Dataset for Chatbots/Virtual Assistants which serves as its training resource for dialogue generation. The system would need to manage extended dialogues through multiple interactions which would create authentic dialogue patterns that match the dialogue's situation. The system uses sentiment analysis to determine user input tone which ChatGLM-LoRA uses to create automated responses. The system will generate compassionate responses when users show negative emotions or discuss their mental health issues[16].

5.5.4. Model Training and Evaluation

The next step is to train the selected models using the preprocessed datasets. The training process will vary according to which model is being used because BERT and DistilBERT require different training procedures. The loss functions for sentiment analysis and intent classification will guide the optimization of the models. Common evaluation metrics include accuracy, precision, recall, and F1-score. ChatGLM-LoRA: Use the conversational data

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from the chatbot dataset to fine-tune the model on generating relevant and contextually appropriate responses. The evaluation process uses metrics which include BLEU for measuring dialogue quality and user satisfaction to determine assessment results. The trained models will undergo evaluation with a test set which tests their capacity to correctly classify sentiment and determine user intentions and produce dialogue responses [17].

Real-Time Integration and Deployment

The system becomes operational after its training phase when it can function within a virtual assistant or chatbot system. The project includes the three main components which are: Sentiment Analysis Integration: The BERT or DistilBERT-based sentiment analysis model will analyze user input in real-time to detect emotions (positive, negative, neutral) and possibly identify suicidal thoughts [18][19].

Intent Classification

The user request information assessment and user support request and user request classification will be performed by DistilBERT. The system uses ChatGLM-LoRA to perform its main task of producing dynamic responses which match the user's current dialogue while maintaining their previous statements through a process of generating replies that match their previous statements [20]. The system generates responses through sentiment analysis which helps it determine response tone while adjusting empathy levels based on perceived user emotions. The system uses every user interaction as feedback to create new conversational data which enables the chatbot to learn user behavior while improving its response methods.

Continuous Monitoring and Updates

The system requires ongoing evaluation of its operational performance because it cannot function as a permanent solution after its initial launch. The system needs ongoing maintenance which includes periodic model updates using fresh data to adapt to changing user behaviour and developing emotional patterns. Mental-health applications require ongoing development because they need to address new problems which emerge while the system must maintain its ability to detect new patterns and handle different types of distress.

6. Results and Discussions

This section examines the model processes, multiple states, identifies relationship with gender, age to decide which insights can enhance therapeutic methods. The results establish requirements for a scalable data-driven CBT model which must support all emotional and demographic characteristics present in the dataset. The model customizes its functions to different user groups by providing personalized results because it identifies emotional differences which exist between different age groups and different gender groups. The analysis of sentence length diversity demonstrates that the bot can manage multiple user input styles which will enhance its effectiveness as a therapy tool used in real-time. The graphs provide different interpretations of male and female CBT behaviour in The graphs present multiple interpretations of CBT behavioural patterns that show different ways of understanding male and female behaviours in CBT. The study analyses social media posts which number at 38,000 to assess their impact on human mental health by providing solutions and exercises that promote healthy living. The below data also shows the yearly increase in posts on social media regarding the cognitive emotions these data sets would be helpful for the easy understanding of the human thinking and provide a helpful treatement. The study analyzed monthly posts to determine whether male or female participants experienced these emotional states.

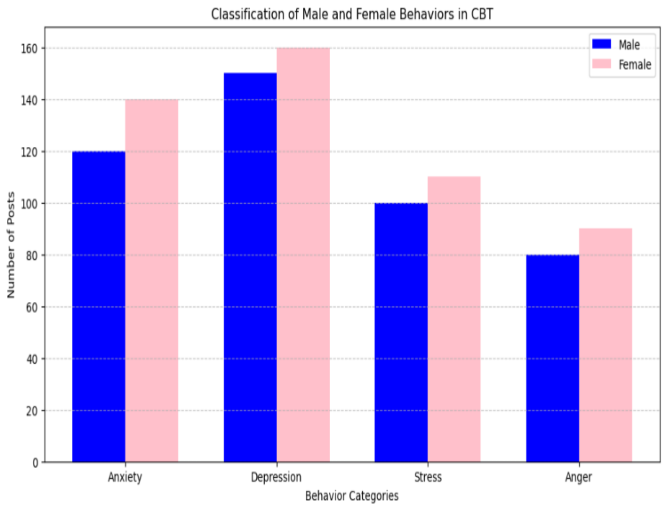

Figure. 1 Classification of Male and Female Behaviors in CBT

From Figure-1 the "Classification of Male and Female Behaviors in CBT" analyzes four different behavior categories, which include Anxiety, Depression, Stress, and Anger. The x-axis shows the behavior categories while the y-axis displays the total number of posts that belong to each category.

The data shows different patterns between male and female users, who display their behaviors through blue bars and pink bars respectively. Both genders contribute meaningfully to the discussion, though women post slightly more often, and in the category with the highest activity, their presence stands out even more; even in the mid-range category, where the number of posts drops to a moderate level, women still outpace men, a pattern that continues in the category with the fewest posts overall. The layout of Figure-2 uses an x-axis which displays four behavior categories and an y-axis which shows the

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complete number of negative posts associated with each category. The bars show a hierarchy which becomes evident to the viewer immediately.

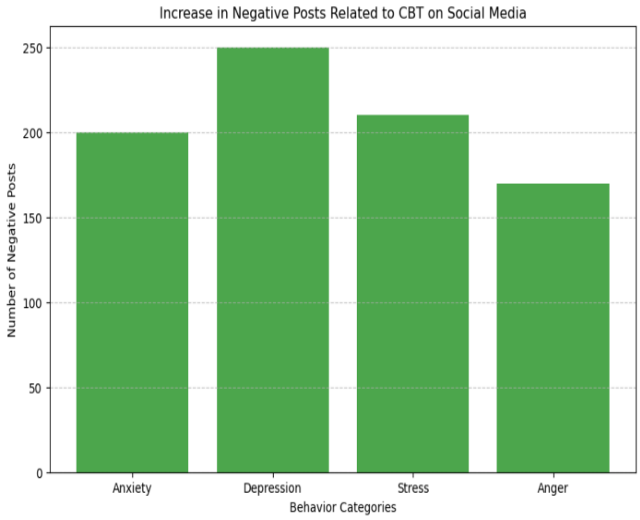

Figure. 2 Increase in Negative Posts Related to CBT on Social Media

The largest increase appears in Depression which reaches a level beyond all other conditions while Stress and Anxiety show moderate levels and Anger maintains a level which falls below all three conditions. The distribution shows that certain difficulties remain active throughout CBT because certain areas need specialized assistance. The study of these patterns reveals to us which areas users find most difficult while showing us how their mental health develops throughout time.

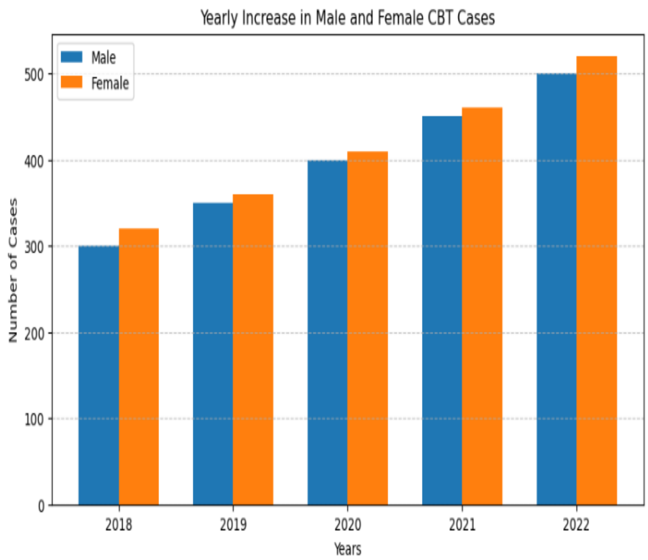

Figure. 3 Yearly Increase in Male and Female CBT Cases

The x-axis of Figure-3 shows all the years between 2018 and 2022 while the y-axis displays the total number of men and women who reported using CBT in each year. The two groups show different usage patterns which become visible through the paired bars because both groups show increasing usage throughout the entire period while women maintain a slight edge over men.

The gap between men and women indicates that women show more readiness to discuss their mental health problems and to find help than men do. The trends in this research provide clinicians and policymakers with valuable information because they show which areas need improvement and which areas already show strong performance while displaying how future mental health programs should be developed to fulfill public needs.

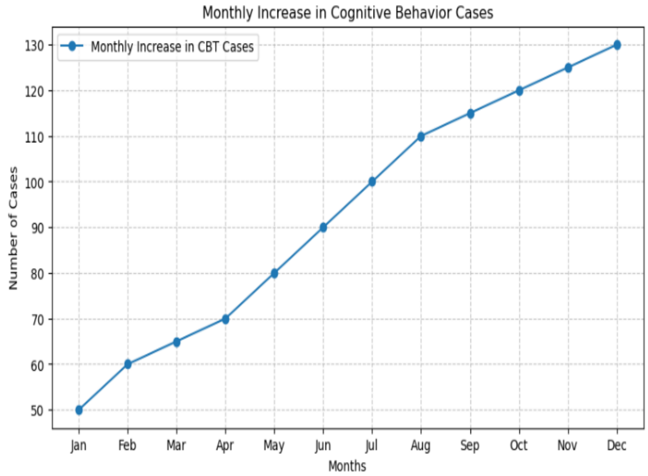

Figure. 4 Monthly Increase in Cognitive Behavior Cases

The x-axis of Figure-4 displays month intervals which start from January and continue until December. The line chart makes the pattern clear because case numbers increase throughout the year until they reach their peak level during December. The observed rising trend suggests that seasonal factors affect the situation because increased work and school obligations combined with holiday-related stress create additional pressure. The identification of these patterns enables therapists and support teams to forecast peak demand times which assists them in planning their staffing needs and resource requirements before the actual time.

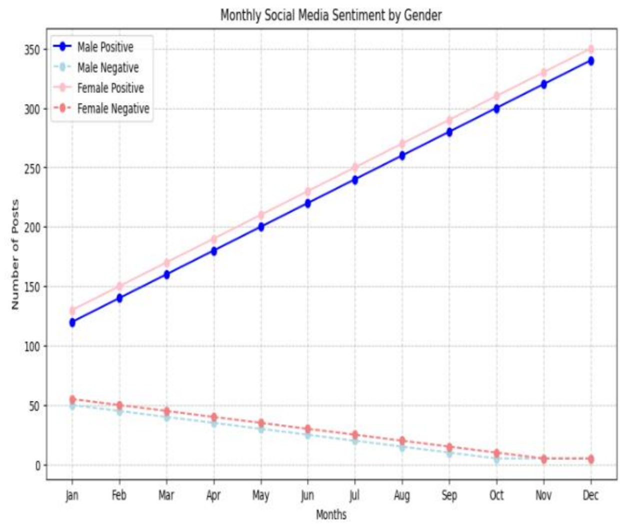

Figure. 5 Monthly Social Media Sentiment by Gender

From figure-5, Both male and female positive sentiment posts show a steady increase throughout the year. Male positive sentiment posts consistently

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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.

Trends: The overall trend indicates that positive sentiment posts dominate throughout the year for both genders. The gradual decline in negative sentiment posts shows that people have begun to show better moods as time passes. The graph demonstrates how people change their emotional responses throughout the year by showing their movement toward positive social interactions.

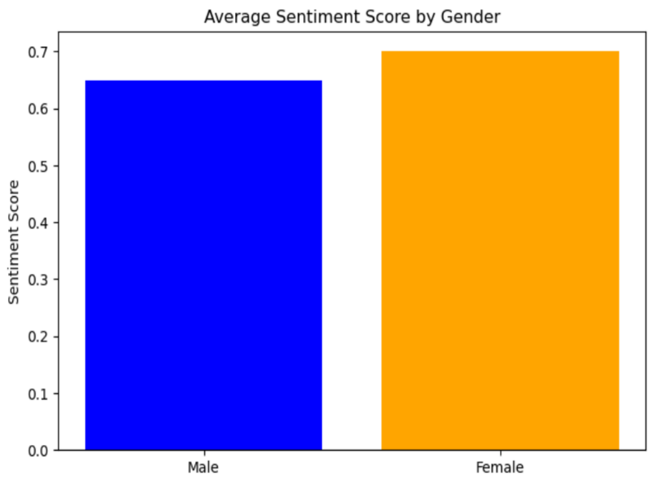

Figure. 6 Average Sentiment Score by Gender

From figure-6, the x-axis displays two gender categories which are Male and Female, and the y-axis displays the average sentiment score for posts which are linked to CBT. Posts receive sentiment scores which range from -1 to +1 to show their emotional tone. This visualization shows how different genders express their positive and negative feelings about posts which relate to CBT. The results show that both genders display positive sentiment toward CBT which indicates that people hold a positive view of this treatment.

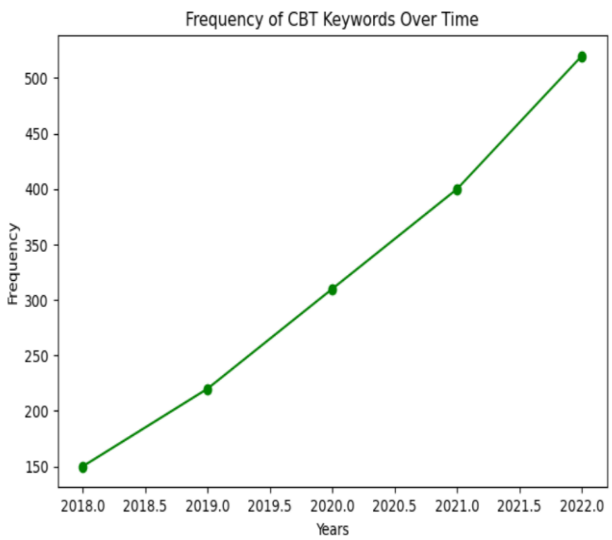

Figure. 7 Frequency of CBT keywords Over Time

The x-axis of figure-7 limits its measurement between the years 2018 and 2022 while the y-axis shows the count of social-media posts that include CBT-related keywords; the line graph shows an upward trend of these mentions because more people became aware of CBT and talked about it more often. The visualization enables researchers to track changes in mental-health research interest through different time periods because mental-health research showed continuous growth which researchers planned to study through two main drivers: global mental-health initiatives that prompted people to seek assistance and the COVID-19 pandemic which increased stress levels that led more people to search for therapeutic solutions and related terminology online.

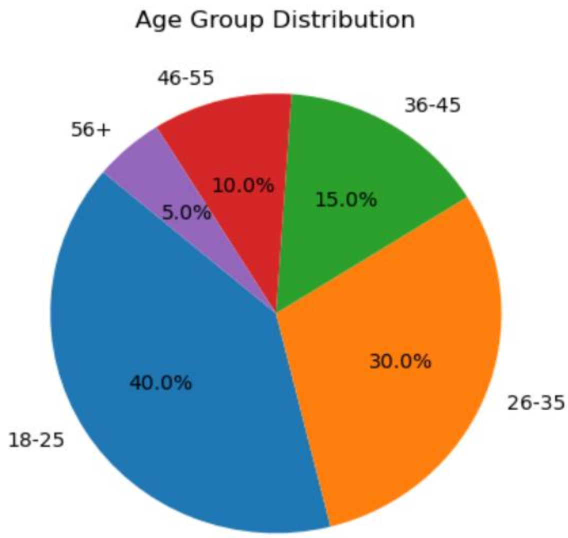

Figure. 8 Age Group Distribution

The pie chart in figure 8 displays the age distribution of social media users who share content about cognitive behavioral therapy. The chart shows that people aged 18 to 25 participate in social media CBT posts more than any other age group while people aged 26 to 35 form the second most active posting group. Online discussions about mental health and cognitive behavioral therapy see much higher participation from younger users than from older users which enables developers to create educational materials and therapy resources that target the most active audience, thus increasing their chances of achieving meaningful interactions and improved treatment results.

The chart in Figure 9 uses horizontal bars to display which regions create the highest number of social media posts about CBT. The x-axis displays the regions of North America Europe Asia and other regions while the y-axis presents the total post count from each region. North America stands out as the region with the highest post count while Europe follows as the second most active region. Other regions exhibit lower posting activity which might indicate differences in public

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understanding and mental health resource availability and online discussion comfort levels.

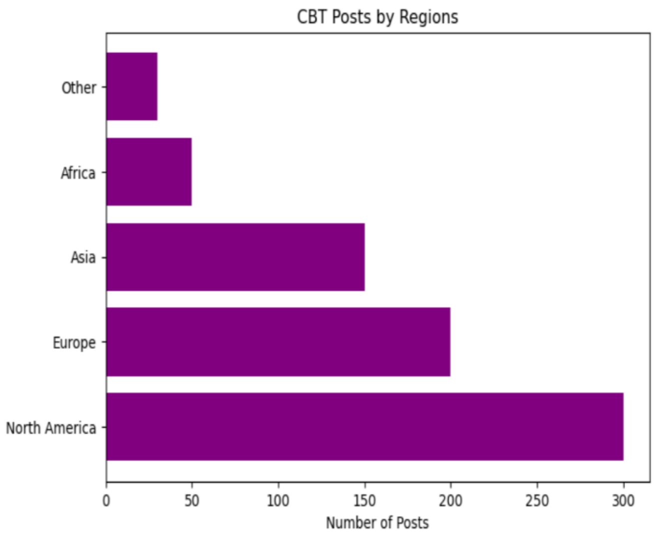

Figure. 9 CBT posts by Regions

The geographic spread of CBT discussions shows organizations which areas need more educational or outreach efforts at present. The accuracy of the mental health assessment enables security teams to determine the mental health needs of their users based on their assessment results.

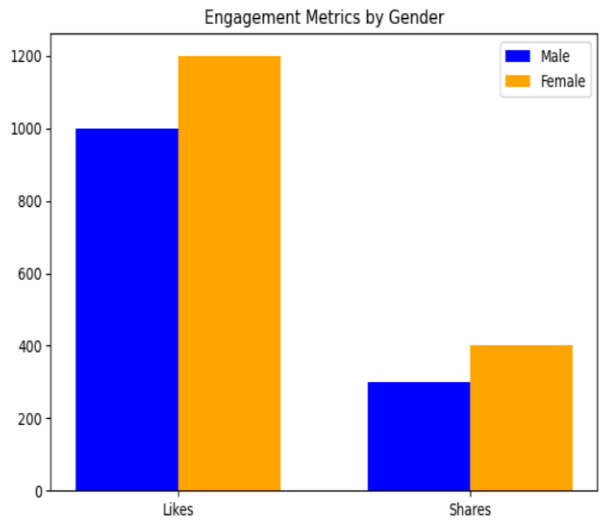

Figure .10 The distribution of Likes, Shares - Engagement Metrics By Gender

The chart from Figure-10 shows different engagement types through its three columns which represent likes shares and other reactions while the y-axis displays the total number of interactions. The bar chart displays two sections which show how male and female users react to CBT-related content.

The main thing that stands out is the gap: posts from female users consistently draw more likes and shares than those from male users. The content of their work allows them to build better connections with their audience because their social networks participate more actively in mental health conversations. The chart shows different engagement patterns between men and women who interact with CBT posts because they use social media to share mental health information.

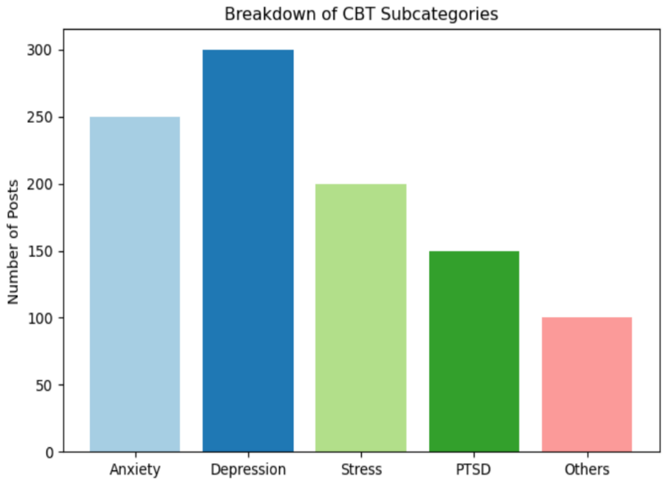

Figure. 11 Breakdown of CBT Subcategories

The x-axis of Figure-11 displays the main CBT subcategories which include Anxiety and Depression and Stress and PTSD, and a larger category called Others. The y-axis displays the number of posts which correspond to each of the subcategories. The bar chart displays an understandable pattern which shows that most online discussions about help-seeking behavior originate from anxiety and depression topics. People discuss Stress and PTSD and other miscellaneous topics less frequently which results in lower awareness about these issues together with uncertainty about their symptoms and a decreased willingness to share their experiences. Mental health professionals use this type of analysis to identify which online mental health issues receive most attention and which less popular topics need extra outreach and support and educational programs.

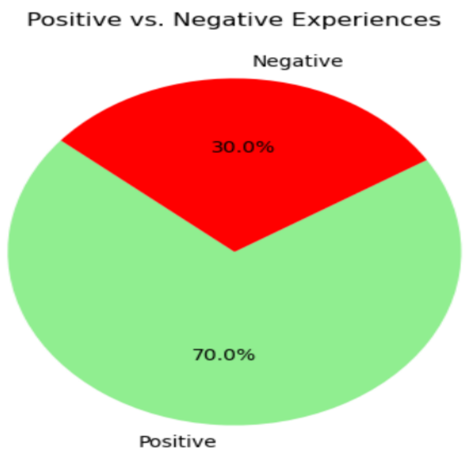

Figure .12 Positive vs Negative Experiences

The pie chart from Figure-12 divides the data into two

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main parts which show that 70 percent of posts are positive while 30 percent of posts are negative. Users describe CBT through positive descriptions which show their gained benefits from therapy while a smaller group of users shows their mixed experiences that need specific support through advanced therapy. This type of overview provides therapists with an effective tool to assess user progress which enables them to adjust treatment methods while predicting upcoming therapy challenges.

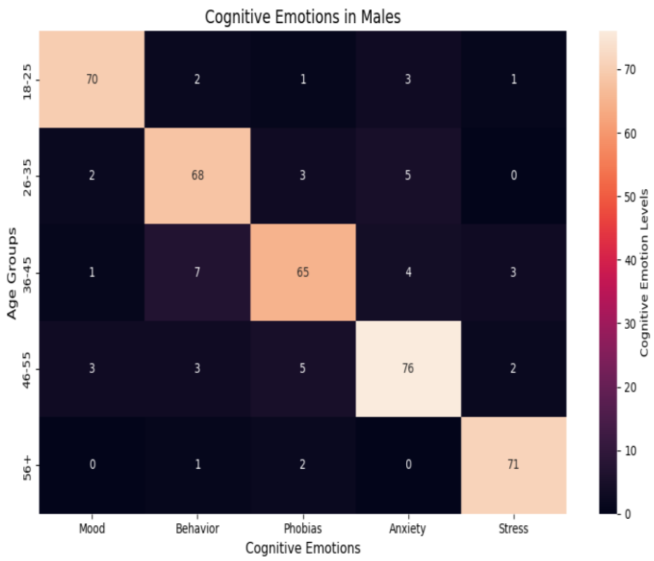

Figure. 13 Age Groups vs Cognitive Emotions in males

The map in Figure-13 shows how men experience cognitive and emotional difficulties through their different stages of adult development. The x-axis displays five key areas of CBT treatment which include Mood Behaviour Phobias Anxiety and Stress. The y-axis separates men into age groups which include 18 to 25 26 to 35 36 to 45 46 to 55 and 56+. The comparison of emotional patterns through different age groups shows researchers which psychological issues become most visible during certain life stages.

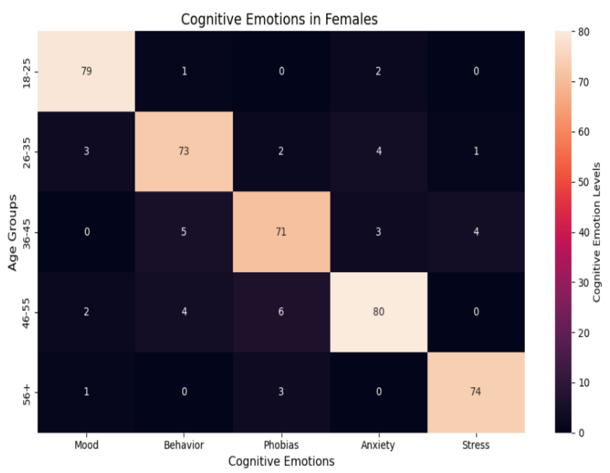

Figure . 14 Cognitive Emotions in Females.

The colour bar on the right section shows how to understand the shading which uses light colours to show higher cognitive-emotion levels for each age group and dark colours to show lower cognitive-emotion levels. The numerical values in each cell provide exact measurements which combine with the colour gradient to show the complete pattern more clearly.

From Figure-14, the male map shows two major differences which can be seen in this comparison. The 18-25 age group shows that females have a higher rate of mood disorders while anxiety levels reach their highest point during the 46-55 age range which exceeds male anxiety levels. Women experience increased stress levels throughout the 56 age range while men display consistent stress levels throughout all age brackets. Women who belong to the 26-35 age range show more severe behavioural problems than men in the same age group. The existing differences demonstrate that clinicians need to create gender-specific treatment approaches for their CBT therapy programs.

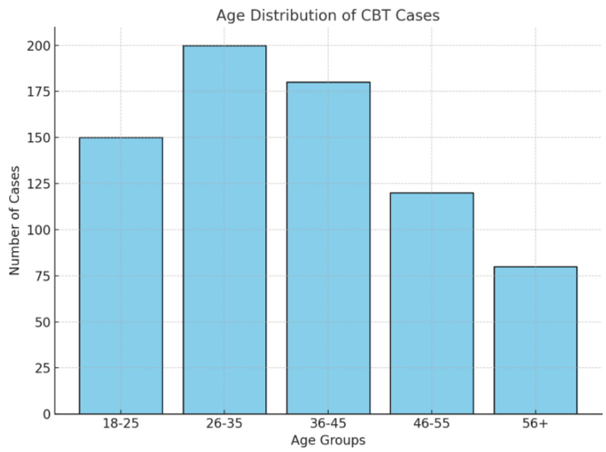

Figure. 15 Age Distribution of CBT Cases

The graph in Figure-15 shows how CBT cases are distributed among different age groups, which helps identify the times when people generally experience mental health issues throughout their lifespan. The 18–24 age group shows the highest rates of occurrence because they face the multiple challenges that accompany their transition into adulthood, which includes academic demands and new workplace experiences and their typical emotional rollercoaster.

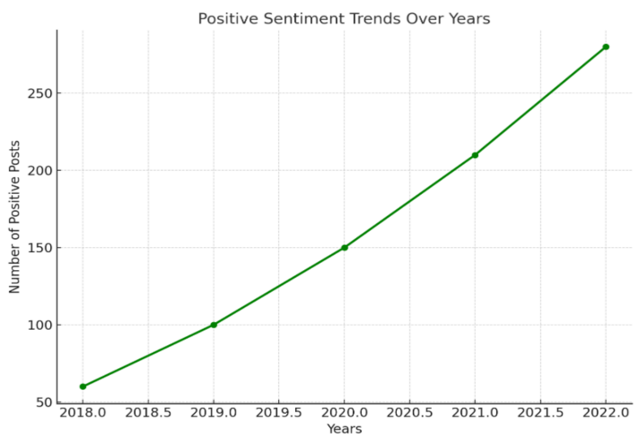

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Figure. 16 Positive Sentiment Trends Over Years.

The middle-aged group, roughly ages 25–40, shows more even levels, which show their ongoing family commitments and job pressures and financial obligations that combine to create their unique life situation. The numbers start to drop after age 50, which might indicate reduced overall case numbers, or it might suggest that senior citizens spend less time on the Internet and more time keeping their personal information private. The identification of these age-related patterns enables the development of CBT approaches, which match the specific difficulties that individuals encounter throughout different life stages, thus increasing the effectiveness and precision of therapeutic interventions. The graph shows that social media users have developed increasingly positive attitudes towards CBT since the start of each year because public acceptance of mental health treatments has developed into standard practice.

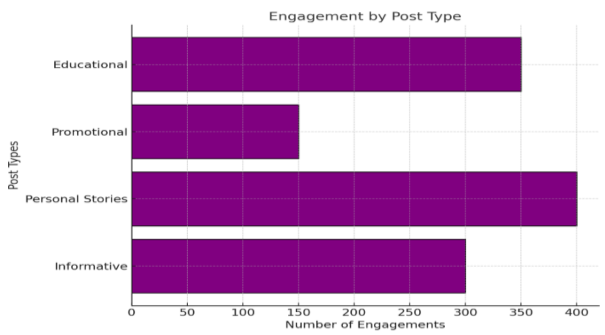

Figure. 17 Number of Engagements by Post Type.

From Figure-17, the bar graph shows how many people interacted with different CBT-related social media posts. The posts contain four types of content which include questions and motivational quotes and personal stories and useful information. Users want to learn more about CBT methods and mental health, so the posts that get the most engagement are the ones that teach them something. Personal stories attract strong attention because they establish emotional bonds with readers who want to belong to a community.

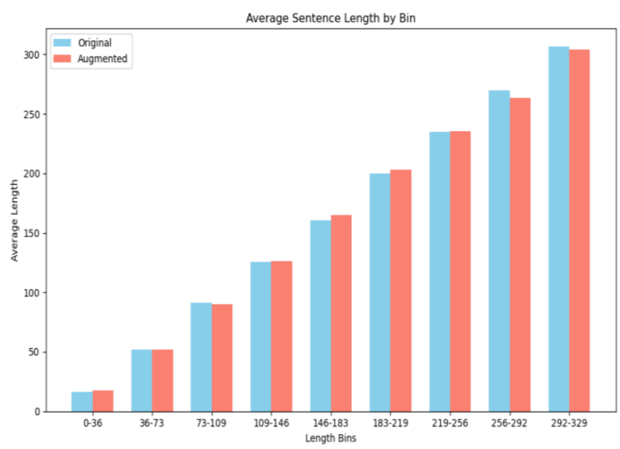

Figure. 18 Average Sentence length by Bins

Figure 18 shows how the average sentence lengths in the Original and Augmented datasets compare across nine length bins, from very short sentences (0–36) to the longest ones (292–329). The two series track each other almost perfectly, with only small bumps here and there slightly higher averages for the augmented data in the mid-range bins and tiny dips at the far end.

The increasing acceptance of CBT treatment demonstrates that more people consider its effectiveness while they abandon their previous belief that seeking treatment should be avoided. The positive sentiment increase results from online awareness initiatives combined with community support systems and educational programs which have created safer environments for people to discuss mental health issues. The established patterns provide researchers and practitioners with a reliable foundation which they can use to develop new methods that will enhance mental health dialogue quality in the future.

7. Conclusion and Future Scope

Cognitive Behavioural Therapy (CBT) already packs a punch by helping people spot and rewrite the mental scripts that sabotage their mood, but the moment you add an AI-driven Posibot into the mix one that chews through language patterns in real time you get something far more agile, a system that can read emotional currents like sadness, anxiety, anger, or even those rare bursts of optimism, then fire back responses crafted to nudge users out of their usual cognitive ruts; this kind of engine doesn't just spit out generic advice, it adapts to the quirks of each person, recognizing that men and women often navigate emotional storms differently, and it scales effortlessly in ways traditional therapy simply can't, mostly because humans can't manually parse endless transcripts or crunch hierarchical text classifications, sentiment signals, and summaries without burning out, whereas the Posibot taps into the ABCD framework to untangle irrational beliefs and behavioural loops, turning the chatbot into a sharp, always-awake assistant capable of guiding users through exercises, offering grounded advice, and supporting those dealing with everything from phobias to depression to runaway anxiety while giving people who can't access therapy an entry point that feels immediate, conversational, and surprisingly human.

The future of CBT tech feels like it's about to blow its own ceiling off, especially as the bot starts pulling in multimodal clues from typed confessions to shaky voice notes to the micro-expressions people swear they're hiding—to build a sharper picture of what someone's actually feeling, and once it starts folding in feedback loops that tweak therapy sessions based on how a user interacts, you get coping strategies that feel

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hand-stitched rather than mass-produced; imagine the bot syncing with wearables, quietly watching heart rate spikes and stress dips, then responding with the kind of real-time guidance a human therapist can't always deliver, and layer on the next wave of language models that can finally pick up sarcasm, cultural nuance, and the metaphors people use when they're trying to talk around their pain, plus multilingual capabilities that let CBT travel across borders without losing its grounding, not to mention VR and AR exposure sessions where a therapist can dial up or ease off a controlled environment like they're adjusting stage lighting this all pairs with healthcare infrastructure upgrades such as large-scale deployment, clean EHR integration, and smooth collaboration with clinicians, while ethical AI safeguards, privacy armor, and automated crisis detection keep the system trustworthy; add gamified progress, community support spaces, and long-term tracking that quietly predicts when someone might need help before they ask, and you end up with a therapy ecosystem powered by GPT-4, ERNIE-style summarizers, and hybrid rule-plus-deep-learning engines that stomp out incorrect medical claims, process emotional cues from speech tone and facial micro-movements, weave in physiological markers like heart-rate variability, and lean on ACT principles to deliver precision that actually moves the needle for people who need it most.

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