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**COURSE: COMPUTER SCIENCE.**

**RESEARCH TOPIC: APPLYING NATURAL LANGUAGE PROCESSING FOR MENTAL HEALTH SUPPORT.**

**REPORT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE IN A PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE IN BACHELOR OF SCIENCE COMPUTER SCIENCE.**

**NAME OF SUPERVISING LECTURER: MR DAVID NCHUNGE.**

**JANUARY-APRIL, 2025**

# DECLARATION

I Caroline Waiyego Wairagu declare that this is my original work and has not been presented anywhere else for academic purpose.

Sign…………………………. Date ………………………………….

**Recommendation**

This seminar report has been submitted for examination with my approval as the university

supervisor.

Signature: ……………………………… Date: ………………………….

# DEDICATION

I dedicate this report to the one who has given me strength and guidance throughout my journey. To the Almighty, thank you for your unending love and grace. Your wisdom and blessings have been my light and shield. I also dedicate this report to my family and friends, who have been my source of inspiration and support. Your encouragement and motivation have been the driving force behind my accomplishments

# ACKNOWLEDGEMENT

First and foremost, I express my deepest gratitude to my Lord, Almighty God, for bestowing upon me the strength and courage to embark on this project with unwavering enthusiasm and dedication. Without His grace, none of this would have been possible, and I am truly thankful for His blessings.

I would like to extend my heartfelt thanks to my esteemed Supervisor, Mr. David Nchunge, who has been an invaluable source of guidance and support throughout this project. His profound insights, constructive comments, and thoughtful feedback have been instrumental in shaping the quality and direction of my work. I am truly grateful for his mentorship and expertise, which have enriched my understanding and helped me to excel in this project.

I am also deeply grateful to the Head of Department and all the lecturers who have generously provided their valuable advice and suggestions throughout the course of this project. Their expertise and wisdom have been instrumental in refining my research and enhancing the overall quality of my work.

Lastly, I am also grateful to my parents and siblings for their unconditional love and unwavering support. Their constant encouragement, understanding, and sacrifices have been the foundation of my academic journey, and I am deeply thankful for their unwavering belief in me.

# ABSTRACT.

This research project looks into the use of natural language processing (NLP) in mental health support. It focuses on identifying early signs of mental illness, assessing the usefulness of current NLP applications, and examining implementation ability and problems. This paper evaluates sophisticated strategies for emotion detection from textual data through an extensive literature survey and empirical investigation of NLP algorithms. The results highlight the potential of NLP, especially when LSTM and BERT are used together, to facilitate the early detection of mental health problems. Nevertheless, the study also draws attention to issues with cultural differences, privacy concerns, and bias in training data, highlighting the necessity of ethical implementation and collaboration between disciplines. The development of guidelines for responsible usage, cooperation between NLP specialists and mental health professionals, and investigation of innovative methods to improve the efficacy of mental health support systems are among the recommendations for further study and use. All things considered, this study advances our knowledge of how NLP is transforming mental health treatment and emphasizes the significance of ethical issues and interdisciplinary cooperation in maximizing its advantages.

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# DEFINITION OF IMPORTANT TERMS:

* **Natural Language Processing (NLP)**  
  A branch of artificial intelligence focused on enabling computers to understand, interpret, and generate human language. It involves techniques that process and analyze large amounts of natural language data.
* **Mental Health**  
  A state of emotional, psychological, and social well-being that affects how individuals think, feel, and act. It includes the presence or absence of mental disorders like depression, anxiety, and PTSD.
* **Sentiment Analysis**  
  An NLP technique used to determine the emotional tone behind a body of text. It classifies text into categories such as positive, negative, or neutral, helping to detect mood changes and emotional states.
* **Text Classification**  
  The process of automatically categorizing text into predefined labels or groups. In mental health applications, it can be used to identify linguistic patterns or symptoms related to specific conditions.
* **Long Short-Term Memory (LSTM)**  
  A specialized type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. It is particularly effective in handling time-series or text data where context over long intervals is important.
* **Bidirectional Encoder Representations from Transformers (BERT)**  
  A state-of-the-art NLP model developed by Google that uses transformer architecture to capture context from both the left and right sides of a word in a sentence, enhancing understanding of nuanced language.
* **Support Vector Machine (SVM)**  
  A supervised machine learning algorithm used primarily for classification tasks. It works by finding the optimal hyperplane that best separates data into different categories.
* **Logistic Regression**  
  A statistical model used for binary classification tasks. It estimates the probability that a given input belongs to a particular category, making it useful for baseline comparisons in text classification.
* **Random Forest Classifier**  
  An ensemble learning method that builds multiple decision trees and merges their results to improve classification accuracy and robustness. It is well-suited for handling high-dimensional data.
* **Machine Learning**  
  A field of artificial intelligence that focuses on developing algorithms that can learn patterns from data and make predictions or decisions without being explicitly programmed for each specific task.
* **Deep Learning**  
  A subset of machine learning that uses neural networks with many layers to model complex patterns in data. It underpins advanced NLP models like BERT and LSTM.
* **Transformer Architecture**  
  A neural network design that uses self-attention mechanisms to process input data in parallel, significantly improving the efficiency and effectiveness of NLP models, such as BERT.
* **Topic Modeling**  
  An unsupervised learning technique used to discover abstract topics that occur in a collection of documents. It helps to reveal hidden themes and patterns within large text datasets.
* **Ethical Considerations**  
  In the context of NLP for mental health, this refers to issues like data privacy, confidentiality, informed consent, and the need to address bias in training data and algorithms, ensuring that the technology is used responsibly.

# CHAPTER ONE: INTRODUCTION

## BACKGROUND OF THE STUDY

The fast-developing field of artificial intelligence known as "natural language processing" (NLP) aims to make it possible for computers to understand, interpret, produce, and react to human language in a way that is unrecognizable from human-to-human conversation. Utilizing developments in computer science, mathematics, linguistics, and engineering, natural language processing (NLP) is a collection of complex methods for extracting meaning from written or spoken words and converting them into structured representations that can be automatically analyzed. The main idea behind NLP is to make it easier for people to get information and for computers to understand us better.

Mental health refers to our emotional, psychological, and social well-being, which has a significant impact on how we think, feel, and behave. Many people worldwide suffer from disorders such as depression, anxiety, and post-traumatic stress disorder (PTSD). But, even though mental health is really important, it's often hard to understand, diagnose, and treat problems. Even though more people need help, stigma and a lack of trained professionals make it difficult to get care. Individuals facing mental health issues frequently face a complicated web of challenges, including fear of judgment, restricted access to therapists and expensive treatment costs. This might result in delayed diagnoses, insufficient therapy, and increasing symptoms.

According to the World Health Organization, one out of every four people will suffer from mental or neurological condition at some point in their lives. In the United States alone, about 40 million adults experience mental illness each year (NIMH» Mental Health Information, n.d.). The stigma associated with mental health, as well as a shortage of skilled experts, exacerbates the situation. According to a 2020 research conducted by the National Alliance on Mental Illness (NAMI), just 41.5% of adults with mental illnesses received treatment in the previous year.

These statistics demonstrate the critical need for innovation in mental health delivery. Traditional services frequently have limits in terms of accessibility, scalability, and detection. Therapists are frequently concentrated in cities, leaving rural people with inadequate access to healthcare. Furthermore, the typical therapeutic model can be time-consuming and costly, making it inaccessible to many people. Early diagnosis of mental health issues is critical for improving long-term results, yet traditional approaches frequently rely on self-reporting or subjective assessments.

However, Natural language processing (NLP) has emerged as a potential game changer. NLP enables computers to interpret and process human language, opening the door to new applications that can benefit mental health. Consider a world in which technology can analyze massive volumes of text data, detecting minor alterations in language that may suggest the early stages of mental illness. NLP has the potential to transform mental healthcare delivery by providing earlier intervention, personalized assistance, and greater access to mental health services.

Researching the applications of NLP in mental healthcare is important. Early detection and treatment are crucial for improving long-term mental health outcomes and NLP offers the ability to detect at-risk individuals earlier. This could result in reduced symptom severity, lower healthcare expenses and a general improvement in public health. NLP-powered applications can potentially help to bridge the healthcare access gap by providing support and information to marginalized groups. By studying language patterns, NLP can even assist to adapt therapy techniques for individuals, perhaps leading to more effective outcomes. Furthermore, incorporating technology into mental healthcare via NLP may normalize getting treatment and eliminate the stigma associated with mental illness, enabling more individuals to seek the help they require.

The field of NLP in mental health is still in its early phases, but it has enormous potential for the future. As NLP technology advances, we should expect to see increasingly more sophisticated applications emerge, providing a broader range of support and intervention choices for people dealing with mental health issues.

## 1.2 PROBLEM STATEMENT

Despite increasing awareness of mental health issues, there is a significant gap in offering accessible and effective assistance programs, particularly in areas with limited resources. Traditional approaches to mental health care usually rely heavily on personal visits with mental health specialists, which may not be affordable or accessible to everyone in need. Furthermore, the stigma surrounding mental illness serves as a barrier, inhibiting people from seeking treatment. As a result, there is an urgent need for innovative solutions that employ technology, particularly Natural Language Processing (NLP), to bridge these gaps and provide personalized, stigma-free mental health support services.

## 1.3 OBJECTIVES OF THE STUDY

### 1.3.1 General Objective

To explore and evaluate the application of Natural Language Processing (NLP) techniques in enhancing mental health support services by improving early detection, diagnosis, and accessibility to personalized, scalable, and stigma-free care.

### 1.3.2 Specific Objectives

The specific objectives of this study are as follows:

1. To create a framework for detecting early indicators of mental illness by using natural language processing techniques to text-based data such as electronic health records.
2. Using machine learning algorithms to detect linguistic patterns linked to certain mental health problems, such as depression and suicide ideation.
3. To propose an integrated model combining NLP techniques with traditional mental health support systems to enhance accessibility and personalization of care.

## 1.4 SCOPE

The research is going to focus on text-based mental health detection using NLP. Although speech recognition based on natural language processing has been researched in the context of mental health diagnosis, text-based analysis of social media and electronic health records is a relatively recent technology with several therapeutic implications. The research will look into many sorts of mental health problems, sentiment and semantic analysis theories and practices, understanding of the call language and how computers comprehend it, machine learning theories and practices, social media, and health data analytics

The research will also encompass recognizing user's hidden qualities and predictions, theory and practices of data retrieval from the web and how NLP technology will be employed in the process of building mental health diagnostic aids. The primary goals of this study are to investigate the potential of using natural language processing methods rather than traditional methods such as regular expressions; to analyse and identify the best models and features in sentiment and semantic analysis; and to investigate the relationship between various types of mental health problems and linguistic elements, with a focus on depression and suicidal behaviour. The study's goal is to train machines to understand human communication, such as language, and to aid in the detection of mental illnesses.

By investigating the use of natural language processing technology in the mental health area, I will not only gain machine learning skills in the IT field, but I will also be able to facilitate and improve clinical practice in mental health diagnosis.

## 1.5 SIGNIFICANCE

This study on Natural Language Processing (NLP) techniques in mental health assistance has major effects for both society and the growing body of knowledge in mental health treatment. Using sophisticated NLP approaches, the project aims to address significant issues with like accessibility, affordability, and effectiveness of mental health measures particularly for those with limited resources. If successful, the outcomes of this study could significantly change the way mental health treatment is delivered by providing scalable, tailored, and non-stigmatizing support services. The use of modern NLP algorithms to massive amounts of textual data generated from multiple sources such as social media platforms, online forums, or clinical records can result in a better understanding of mental health conditions. Researchers and clinicians will benefit greatly from the quantity of information contained in these databases, providing for a better understanding of the nuances and complexities inherent in mental diseases. Improved diagnostic precision, personalized treatment regimens, and proactive intervention strategies are just a few examples of how a better understanding of mental health concerns can benefit patient care and long-term outcomes.

Furthermore, applying NLP algorithms to detect early warning signals and preemptive indicators of psychological discomfort in written communication may allow for earlier interventions. Timely identification of persons at risk would enable faster referral paths and preventative measures, reducing unnecessary suffering and boosting positive outcomes.

Furthermore, deploying NLP-centric mental health support mechanisms enables the opportunity to avoid common barriers connected with traditional mental health services, such as space constraints, high prices, and deep-seated cultural biases against seeking professional help. Remote consultations, inexpensive price structures and digitally mediated interactions reduce many of these barriers, making mental health treatments more accessible and less daunting to potential patients. Additionally, NLP-enhanced mental health services promote self-management skills in end users, giving them more control over their emotional well-being. Individuals equipped with these cutting-edge technologies can precisely monitor their progress, see changes in their affective states, and actively participate in evidence-based practices at their leisure, resulting in increased self-awareness, tenacity, and autonomy. Despite the numerous benefits provided by NLP applications in mental health, there are still several ethical quandaries about confidentiality, informed consent, and prejudiced algorithmic decision-making processes. Engaging in this line of study will help develop severe norms, standards, and legal parameters to protect user welfare, confidence, and fair portrayal.

# CHAPTER TWO: LITERATURE REVIEW.

## 2.1: INTRODUCTION.

Traditional approaches to evaluating mental health frequently depend on clinical assessments or self-reporting, which can be expensive, time-consuming, and subjective. Growing interest has been shown in using technology, especially Natural Language Processing (NLP), to offer scalable, affordable, and easily accessible mental health support options in recent years.

NLP, a branch of artificial intelligence that studies how language functions in human-computer interaction, has special possibilities for the analysis and comprehension of textual information pertaining to mental health. NLP approaches can help in early detection, targeted intervention, and ongoing support for those with mental health difficulties by extracting linguistic features, detecting emotional cues, and recognizing patterns in language use.

The goal of this chapter is to conduct a critical analysis of the body of research on the use of NLP in mental health support. It will examine several facets of NLP methods, current frameworks, models and gaps in the literature, and suggest a new model to fill these gaps. This study aims to further the development of NLP-based techniques in mental health support by collecting and assessing recent research findings, thereby improving the efficacy and accessibility of mental health services for people all over the world.

## 2.2: LITERATURE SEARCH.

Traditional techniques for detecting mental emotion or stress have generally depended on in-person interviews, self-report surveys or wearable sensors. These approaches, however, are reactive, time-consuming, and frequently fall short of capturing people's mental state changes in real time. The emergence of social media platforms has revolutionized the way individuals communicate and express their feelings, opening up novel avenues for mental health assistance. Reshma Radheshamjee Baheti demonstrated the potential of extracting emotion-related textual data from online communities when she devised a technique that uses sentiment analysis on Twitter datasets to identify stress and enjoyment.

S. Ganesh Kumar and Trinayan Borah investigated the use of machine learning and natural language processing (NLP) in enhancing mental health. They achieved 67% precision and recall using Support Vector Machines (SVM) with N-gram when they extracted sentiment strength from informal English language in online communities using the Tensi Strength framework.

Elsbeth Turcan discussed supervised learning techniques for stress recognition, such as neural and conventional methods, whereas Deepti Patil used human speech analysis to identify emotions, concentrating on vocal inflections that suggested stress.

Disha Sharma used data from over 200 students to evaluate the efficacy of machine learning algorithms in reducing stress risk for university students. The algorithms she used included Naive Bayes, Linear Regression, Multi-layer Perceptron, J48, and Random Forest. Mounika Karna investigated the effectiveness of a Long Short-Term Memory (LSTM) mechanism based on deep learning for textual emotion recognition, outperforming other learning strategies in the process. The Aimens system, developed by Umar Rashid, uses a deep learning-based LSTM model with word2vec and doc2vec embeddings to identify emotions in textual interactions.

Using pre-processed speech input and convolutional neural networks (CNNs) for stress prediction, Dr. S. Vaikole suggested a method to differentiate between stressed and non-stressed responses. Zhentao Xu utilized a multimodal approach, integrating verbal, visual, and metadata indicators from Flickr posts to evaluate mental health, and Prerna Garg applied machine learning models such as Linear Discriminant Analysis, Random Forest, and Support Vector Machine to the WESAD dataset to detect stress.

Varun Sundaram showed forth a cutting-edge method for using TFIDF to detect emotions in text data. This method successfully categorized emotions into six groups. Furthermore, U. Reddy and associates evaluated the degree of stress experienced by IT professionals using the OSMI Survey dataset from the IT sector, underscoring the widespread nature of stress in this area. All of these researches show how NLP and machine learning can be used to identify and treat mental health problems in a variety of settings and demographics.

Other studies have concentrated on text-level emotion extraction from textual data pertaining to suicide and mental health. In an effort to comprehend the emotional content of suicide notes, Pestian et al. (2012) carried out a shared task for emotion mining. Nguyen et al. (2014) took particular interest in LiveJournal entries that talked about depression and associated subjects. Li et al. (2015) looked into stigmatizing and ineffective responses to suicide on the Chinese social media site Weibo, whereas Homan et al. (2014) and O'Dea et al. (2015) found posts expressing suicidal ideation and suffering. Milne et al. (2016) furthered our understanding of discussions related to mental health in online forums by organizing a shared task for recognizing and prioritizing worrisome content on ReachOut.com's peer support forum.

At the author level, Coviello et al. (2014) and Kramer et al. (2014) looked at the dissemination of moods within Facebook social connections, while Sadilek et al. (2013) researched the temporal changes in the mood valence of Twitter users. Using social media data, De Choudhury and colleagues have tried clinical diagnosis for diseases like depression, post-traumatic stress disorder (PTSD), and postpartum depression alongside participants in shared projects hosted by Coppersmith et al. (2015). Furthermore, Homan et al. (2014b) and Masuda et al. (2013) sought to use their online actions to identify people who are now experiencing distress or are thinking about taking their own lives.

Sentiment analysis is the primary method used in population-level studies to quantify mood valence, with a primary focus on data from Twitter and Facebook. Some researchers correlated spatial and temporal fluctuations with external statistics, while Golder and Macy (2011) and Dodds et al. (2011) did observational investigations. For example, surveys of life happiness were compared with sentiment analysis results by Schwartz et al. (2013) and Larsen et al. (2015), whereas depression incidence and antidepressant prescription rates were utilized as benchmarks by De Choudhury et al. (2013b). By contrasting social media data with a number of indices, such as wealth, obesity, and gun violence, Mitchell et al. (2013) shed light on the wider societal effects of mental health trends.

In 2003, Kessler and colleagues initiated a groundbreaking project aimed at examining the frequency and associated factors of mental illnesses in the US, providing significant epidemiological understanding of the state of mental health issues.

In their investigation into the use of social media data analysis for mental health screening and monitoring, Wang et al. (2018) concentrated on the identification of depression symptoms using behavioural and linguistic clues found in Twitter messages. Their research added to the expanding corpus of work that examines the possibilities of internet platforms for monitoring mental health.

Reece and Danforth (2017) investigated the relationship between language usage on Twitter and county-level health outcomes in the US, including rates of depression and other mental health markers. They clarified the intricate connection between online discourse and mental health at the population level through their investigation. In their investigation of the viability of using social media data to forecast suicide risk, Coppersmith et al. (2018) closely examined the language and behavioural indicators linked to suicidal thinking in online posts. Their research shed important light on the possibilities of using computational methods to identify those who are more likely to kill themselves.

Chancellor et al. (2016) examined the complex ways that social media shapes attitudes and actions around mental health. Their research highlighted the significance of appropriate online discourse by illuminating the dual role of online platforms as possible sources of psychological discomfort as well as sources of assistance. Using smartphone sensor data, Abdullah and Choudhury (2019) started a fresh investigation into machine learning algorithms for the prediction of depression symptoms. Their study provided novel approaches to early identification and intervention by fusing passive sensing technologies with mental health assessment.

The complex interactions between college students' use of social media and their mental health consequences were examined by Hswen et al. (2019). They shed important light on the intricate connection between internet behaviour and psychological health through their analysis. The usefulness of digital interventions, including smartphone apps and online platforms, in enhancing mental health outcomes and reducing the symptoms of anxiety and depression was investigated by Bakker et al. (2018). Their research demonstrated the promise of technology-based therapies as scalable and easily accessible instruments for supporting mental health.

In their investigation of the phenomena of emotional contagion on social media platforms, Ferrara et al. (2019) looked at how emotional interactions and expressions spread via online networks and affect users' mental and emotional states. The mechanisms driving emotional dynamics in digital environments were clarified by their exploration.

## 2.3 **OVERVIEW OF NLP IN MENTAL HEALTH SUPPORT**

### NLP Techniques in Mental Health

The overview offers a thorough investigation of the diverse function that Natural Language Processing (NLP) techniques perform in the field of mental health support. NLP is a large and active area that includes a wide range of methods for comprehending and treating mental health-related problems. These methods include sentiment analysis, text categorization, the development of tailored interventions, and more. Every one of these methods makes a distinct contribution to the overall objective of successfully recognizing, diagnosing, and treating mental health problems.

One of the fundamental NLP techniques, sentiment analysis, for example, makes it possible to extract emotional states from textual input. Sentiment analysis algorithms can determine if a text represents positive, negative, or neutral attitudes by examining linguistic patterns and contextual factors. This capacity is extremely helpful when it comes to identifying mood swings, emotional distress, and other signs of mental health problems. Sentiment analysis is a tool that NLP uses to help people at risk receive early intervention and assistance, which lessens the negative effects of mental health issues on their wellbeing.

In addition to that, NLP approaches go further to sentiment analysis to include text classification, which is a critical component in finding behaviours, linguistic indicators, and symptoms linked to particular mental health illnesses. Text classification algorithms help with diagnosis, therapy planning, and outcome prediction for a variety of mental health illnesses by classifying textual input into predetermined classes or labels. This capacity improves the quality of treatment given to people seeking support by empowering mental health practitioners to make well-informed decisions based on the insights derived from textual data.

Moreover, NLP makes it easier to create specific measures that are suited to each person's particular requirements and preferences. Natural Language Processing (NLP) algorithms can produce tailored therapy prompts, recommendations, and interventions to target certain mental health issues by examining linguistic patterns, emotional cues, and behavioural inclinations. These interventions provide a scalable and accessible way to help people manage their mental health and efficiently navigate challenges. They are given through interactive mediums like chatbots, mobile applications, or virtual assistants.

### Applications of NLP

NLP is a flexible technology that may be applied in many different settings to help and promote mental health. NLP is used for more than only sentiment analysis; it may also be used for text classification and the creation of customized interventions, each of which brings something new to the field of mental health assistance.

Sentiment analysis, a basic Natural Language Processing (NLP) method, is essential for interpreting the textual data's emotional tone. Sentiment analysis uses linguistic analysis and computers to automatically classify text into several emotional categories, usually positive, negative, or neutral. This feature is especially useful when it comes to mental health support because it enables academics and practitioners to learn about people's emotional states and mood swings just from the words they say. Sentiment analysis is a useful technique that can be used to uncover linguistic patterns that are suggestive of unpleasant emotions, therefore helping to identify possible cases of anxiety or depression. People who are depressed, for example, could write with a lot of negative emotion, such as melancholy, hopelessness, or despair. Similarly, people who are experiencing anxiety may have elevated negative affect, as seen by displays of concern, fear, or trepidation.

Moreover, the process of classifying textual data into predefined categories, such as symptoms, treatment outcomes, or particular mental health illnesses, is automated using text classification algorithms. These algorithms help with diagnosis, treatment planning, and outcome prediction by recognizing language indications linked to certain mental health issues. Text classification, for instance, can be used to group online chats or therapy transcripts into categories related to mental health, giving mental health practitioners insight into patients' experiences and enabling them to customize interventions (Malgaroli et al., 2023).

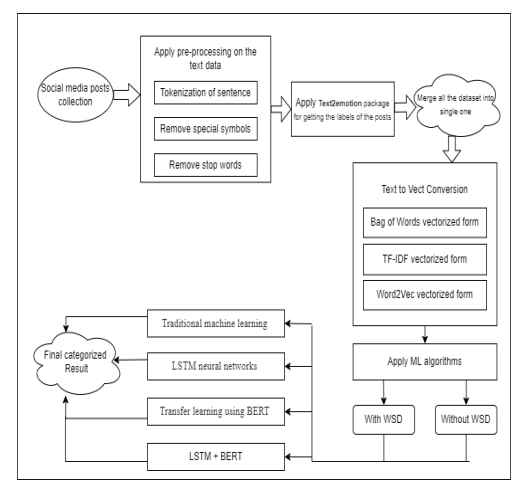


Figure 1 A flowchart for the process of data collection

*Image source: Google Chrome*

Using NLP techniques, individualized therapy prompts, recommendations, and interventions can be developed based on the linguistic preferences, emotional states, and therapeutic needs of each patient. Natural language processing (NLP) systems are able to recognize triggers, coping strategies, and tailored therapeutic interventions based on textual data from online journals, therapy sessions, or self-reports. This tailored strategy improves patient happiness and results by increasing adherence, engagement, and the efficacy of mental health treatment.

Aside from these uses, NLP approaches are also employed in mental health support for language modelling, information extraction, and conversational bots. These apps add to an extensive network of instruments and methods designed to improve the provision of mental health services, encourage early intervention, and assist people in properly managing their mental health.

## EXISTING MODELS AND FRAMEWORKS

1. **BERT (Bidirectional Encoder Representations from Transformers).** BERT is a state-of-the-art NLP model developed by Google that utilizes transformer architecture to capture bidirectional contextual information from text data. BERT was employed for tasks such as sentiment analysis, emotion detection and language generation. Its ability to understand the context of words and phrases in text data makes it particularly suitable for capturing nuanced linguistic patterns indicative of mental health conditions. The high accuracy and performance of BERT in analyzing text data contribute significantly to enhancing the capabilities of mental health support systems.
2. **LSTM (Long Short-Term Memory).** LSTM is a type of recurrent neural network (RNN) known for its ability to model sequential data effectively. In combination with BERT, LSTM further enhances the contextual understanding of text data by capturing long-range dependencies and temporal dynamics. This hybrid approach leverages the strengths of both models, with BERT providing deep contextual embeddings and LSTM capturing sequential patterns. The LSTM+BERT model achieved superior performance in the research, demonstrating its efficacy in detecting and analyzing mental health-related text data.
3. **Support Vector Machines (SVM):** By identifying the ideal hyperplane that maximizes the margin between classes, SVM is a flexible classification technique that performs exceptionally well in classifying data points. SVM can be trained on labelled textual datasets in the context of mental health assistance to categorize text samples into specified groups, including depression, anxiety, or suicidal ideation.
4. **Logistic Regression.** Logistic regression is a classical statistical model used for binary classification tasks. Although it may not be as sophisticated as deep learning models like BERT or LSTM, logistic regression is often employed as a baseline model for comparison in text classification tasks. Its simplicity and interpretability make it useful for understanding the importance of different features in predicting mental health outcomes from text data. In the research, logistic regression may have served as a benchmark against which the performance of more complex models was evaluated.
5. **Random Forest Classifier.** Random forest is an ensemble learning method that constructs multiple decision trees and combines their predictions to make final classifications. In the research, the random forest classifier was likely utilized for its ability to handle high-dimensional data and capture non-linear relationships between features. While random forest classifiers can achieve high accuracy and robustness, they may lack the interpretability of simpler models like logistic regression. Nevertheless, random forest classifiers can be valuable for analyzing text data in mental health support systems, especially when dealing with diverse and heterogeneous datasets.

## 2.5 GAPS IN EXISTING LITERATURE

Although there has been substantial progress in the research, there are still several gaps and difficulties that restrict the efficacy and scalability of NLP-based treatments for mental health assistance. These gaps cover a wide range of topics, such as methodological constraints, contextual awareness, personalization, and ethical considerations.

Individual clinical data analysis, comprising neuroimaging, EEG, and EHR data, as well as social media usage data, has been the main focus of current research in mental health analysis. To give a thorough picture of mental health, there is a notable gap in the integration of various data sources. Through the integration of many data sources, including as neuroimaging, wearable sensor physiological data, and social media behaviour, researchers may be able to obtain a more comprehensive understanding of an individual's mental health condition and risk factors. The intricate interactions between biological, psychological, and social elements that contribute to mental health illnesses may be better understood thanks to this integrated approach.

Wearable medical sensors and social media data are being used more often for mental health analysis, which presents significant ethical and privacy issues. Although there is a lack of agreement and thorough standards for ethical considerations and privacy protection, these technologies present important prospects for early detection and intervention. The responsible and ethical use of personal data in mental health studies requires careful consideration of issues like informed consent, data ownership, confidentiality, and data security. Inadequately addressing these issues could erode public confidence and impede the advancement of innovative mental health research.

Although deep learning approaches have yielded encouraging results in mental health diagnosis, research on the generalization and external validation of these models is still lacking. Using certain datasets, numerous researches have shown the efficacy of deep learning models; nevertheless, it is unclear how well these models work in other contexts and with different populations. To evaluate the generalizability, accuracy, and dependability of deep learning models across various demographic groups, cultural contexts, and therapeutic settings, comprehensive validation studies are required. To guarantee the findings' applicability and efficacy in enhancing mental health outcomes, additional efforts need be made to duplicate the results and confirm the model's performance in actual clinical settings.

## 2.6 PROPOSED MODEL

The proposed approach for employing natural language processing (NLP) to detect mental health issues is made to tackle several significant issues that have been documented in the literature. The lack of personalization in present approaches is a key problem, as generalist therapies may not adequately address the distinct needs and preferences of individuals.

In order to address this, the suggested approach combines cutting-edge NLP techniques with customized intervention tactics, guaranteeing that the support is catered to the unique mental health needs of each individual.

The procedure of gathering and preparing data is crucial to the model. A variety of sources, such as social networking sites, online discussion boards, clinical notes, and digital therapy sessions, are used to collect textual data. After that, pre-processing methods like tokenization, stemming, and stop-word removal are used to this heterogeneous dataset to clean and standardize the textual data and guarantee correctness and consistency in the analysis that follows.   
Techniques for topic modelling and sentiment analysis are then used to glean insightful information from the textual input. Sentiment analysis algorithms identify the emotional states of people and look for signs of mental health conditions like stress, anxiety, or depression. Topic modelling, which makes use of techniques such as hidden Dirichlet Allocation (LDA), simultaneously reveals hidden themes and topics in the data, offering a more profound comprehension of common problems and worries in the population being studied.  
The model's framework relies heavily on machine learning categorization algorithms, which help identify those who may be at risk of mental health illnesses. While unsupervised learning techniques like clustering algorithms help to identify patterns and subgroups within the data, enabling personalized intervention strategies, supervised learning algorithms like Support Vector Machines (SVM) and Neural Networks learn from labelled datasets to automate the detection of mental health issues.

The key component of the suggested model is its capacity to produce customized intervention plans using the knowledge gained from topic modelling, sentiment analysis, and machine learning categorization. These interventions which are painstakingly created to meet the unique requirements and preferences of each individual may include personalized treatment prompts, coping mechanisms, mindfulness exercises, and resource recommendations.

Most importantly, the paradigm fits into clinical practice smoothly, giving mental health practitioners access to and use of NLP-derived insights in their daily practices. Ease of use and use of NLP-generated suggestions in clinical settings are made possible by intuitive interfaces and decision support tools, guaranteeing that the model adequately assists mental health practitioners in their decision-making.

Lastly, a thorough assessment of the suggested model is conducted using established criteria including user satisfaction, sensitivity, accuracy, and specificity. Iterative modifications and enhancements to the model are informed by feedback from mental health experts and individuals receiving help, guaranteeing the model's continuous growth and efficacy in tackling the intricate problems of mental health diagnosis and support.

# CHAPTER THREE: RESEARCH METHODOLOGY

## 3.1 RESEARCH DESIGN

This research employs an exploratory research method to examine the effectiveness of using Natural Language Processing (NLP) for mental health support. This design makes it possible for an investigation to be adaptable and flexible, considering the various points of view and the topic's various aspects. Since NLP application in mental health support is still in its infancy as a discipline, it lacks well-established frameworks and complete understanding, which makes exploratory research a perfect way to advance inquiry and produce fresh discoveries.

This involved the following:

1. Review of the Literature- This entails closely examining academic materials including journals, research papers, and technical reports to clarify existing practices, difficulties, and performance indicators. In order to identify research gaps, formulate research questions, and shape the research technique, the literature review will be an essential first step.
2. Authentic Research- To gather unique data from authentic sources, empirical research techniques will be utilized. It involves collecting authentic data on mental health, including self-reported attitudes, clinical records, and textual material from social media platforms. The training, testing, and assessment of NLP models for mental health analysis will be greatly aided by this data.
3. Documentation Review- This section will involve an examination of pertinent written materials, reports, and records pertaining to NLP procedures, mental health conditions, and therapeutic interventions. The objective of this documentation study is to extract knowledge about current approaches, optimal procedures, and obstacles in the field of NLP for mental health assistance.

**RESEARCH QUESTIONS**

Question 1: Utilizing NLP for Identifying Early Signs of Mental Illness Through Text Analysis.

Analyzing text data with NLP techniques presents a promising opportunity for the early detection of mental health issues. Linguistic cues, stylistic variations, semantic associations, and syntactic patterns convey vital clues about an individual's psychological status. Machine learning algorithms trained on labeled corpora can identify distinctive traits characteristic of emerging mental health problems, uncovering latent patterns imperceptible to humans. Focusing on social media conversations, electronic medical records, and helpline transcripts, NLP models can pinpoint anomalous changes signaling impending mental health crises. Although accuracy remains contingent on dataset size, quality, and diversity, ongoing advancements in AI and computational linguistics promise increasingly precise predictions.

Question 2: Evaluating Literature on NLP Applications in Mental Health Support

Extensive research supports NLP's role in enhancing mental health support systems. Studies demonstrate that conversational agents powered by NLP can mimic human-like conversation, delivering personalized psychotherapy sessions. Other projects showcase intelligent chatbots supporting veterans dealing with PTSD, adolescents experiencing anxiety, and elderly individuals combatting loneliness. Systematic reviews highlight recurrent themes and challenges faced by developers, such as balancing automation versus personal touch, preserving privacy amidst escalating surveillance fears, and grappling with ambiguous language typical of mental health discussions. Despite notable achievements, standardized evaluation metrics and longitudinal follow-ups remain scarce, impeding definitive assertions about NLP's ultimate utility in mental health support.

Question 3: Strategies for Integrating NLP into Current Mental Health Systems

Capitalizing on NLP's potential requires strategic planning and careful implementation. Firstly, designers must ascertain whether NLP aligns with their vision, considering aspects like desired level of automation, targeted user base, available budget, and staff competencies. Next, they ought to meticulously select appropriate NLP techniques suited for the task, weighing pros and cons relative to alternative options. Addressing privacy concerns becomes paramount, mandating explicit consent forms, encryption, and pseudonymous data handling. Subsequently, extensive pilot testing should occur, accompanied by iterative refinement cycles guided by user feedback and performance metrics. Lastly, scaling NLP implementations warrants cautious attention, accounting for regional dialects, slangs, idiomatic phrases, and culturally bound norms. Collectively, pursuing these steps advances the marriage between NLP and mental health support, yielding mutually beneficial synergies poised to elevate both domains.

Below is the general flow of the research design.

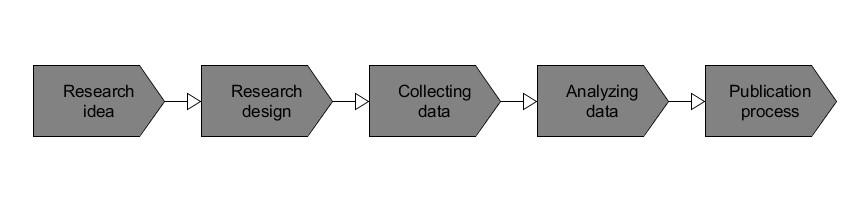


Figure 2 Research Design

The suggested study adopts a bottom-up approach to determine the optimal combination of Natural Language Processing (NLP) approaches for the early detection and intervention of mental health disorders. Beginning with the phase of ideas, the need of using NLP to assess the success of mental health solutions is highlighted. As we go into the design phase, the methodological blueprint takes shape, incorporating empirical procedures such as literary survey, genuine investigation, dossier examination, and reasoning modeling. During the data procurement era, relevant data is gathered, maybe from curated databases, real-world displays, and measurable indices. Moving on to the analytical stage, experimental trials or simulations are conducted to compare the functionality of various NLP algorithms based on their ability to detect and prevent mental health deterioration. Finally, the publicizing stage concludes in the archiving and distribution of research findings via accredited publication outlets, symposiums, or appropriate channels, thereby strengthening the intellectual reservoir dedicated to NLP applications in mental health interventions.

## RESEARCH TOOLS AND PROCEDURES

In order to gain a greater understanding of the effectiveness of Natural Language Processing (NLP) in detecting early signs of mental health illnesses using textual data, I, as the researcher, used a variety of data collection, consolidation, and analysis tools. Due to time constraints, secondary data was the primary source of data collection.

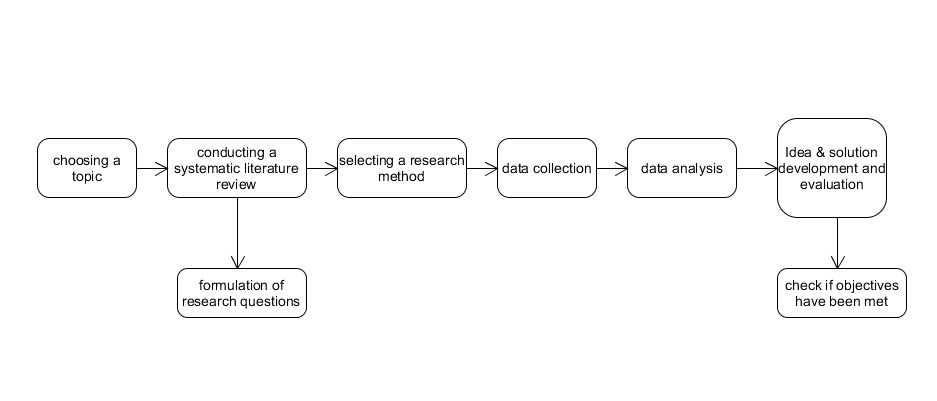


Figure 3 Flow diagram of research procedure

Beginning with data collection, I relied on three sorts of secondary sources: literature reviews, authentic research, and documentation audit. A thorough review of relevant literature allowed me to assimilate current knowledge, familiarize myself with the topic, and identify gaps in the discipline. In addition, I searched through authentic research outputs, capturing raw data, reference datasets, and scoring schemas, establishing the framework for a thorough evaluation. In addition to these efforts, a thorough examination of existing material shed information on current advances, highlighted best practices, and revealed flaws in present NLP tactics designed for mental health diagnosis.

Beyond typical data collection, I assembled a broad array of data modification tools, including numerical software, graphic depiction appliances, and machine learning toolkits. Statistical machines, ranging from simple descriptor figures to complex regression equations and hypothesis screening, understood the curated data, revealed key facts, and gave insightful conclusions. Visual representations in the form of graphs, tables, and layouts enhanced the findings, facilitating interpretation and absorption. I was able to successfully navigate the maze of NLP use in mental health disorder recognition by meticulously integrating secondary data. The production of consistent and validated results, thorough data processing, and cautious interpretation resulted in an important contribution to the growing body of knowledge on NLP utilization in this field.

## TECHNIQUE

* Sentiment analysis: Sentiment analysis algorithms are used to evaluate the textual data's emotional tone and find signs of mental health conditions like stress, anxiety, or depression. By categorizing text into groups based on positive, negative, or neutral sentiment, these algorithms make it possible to identify emotional trends and oscillations.
* Text Classification: Textual data is categorized into predetermined classes or categories related to mental health problems, symptoms, or treatment outcomes using text classification approaches, such as supervised learning algorithms like Support Vector Machines (SVM) and Neural Networks. These algorithms enable the automatic detection and classification of information linked to mental health, by learning from labelled data to categorize text effectively and efficiently.

# CHAPTER 4: RESULTS AND DISCUSSIONS

## 4.1 RESULTS

### 4.1.1 Objective 1: To create a framework for detecting early indicators of mental illness by using natural language processing techniques to text-based data such as electronic health records.

The use of several NLP models to the detection of early indicators of mental disease produce encouraging outcomes. The performance metrics of various classifiers, such as Random Forest, LSTM, BERT, LSTM+BERT combination, Random Forest, Support Vector Machine (SVM), and Logistic Regression, are compiled in Table 1. The accuracy metrics and F1-score show how well each classifier performs in identifying mental health issues.

|  |  |  |  |
| --- | --- | --- | --- |
| **Algorithm** | **F1-Score** | **Accuracy** | **Error rate** |
| **BERT** (Zeberga et al., 2022) | 90.7 | 90.7 | 0.1 |
| **LSTM+BERT** (Zeberga et al., 2022) | *93.3* | *93.3* | *0.1* |
| **Support Vector Machine** (Le Glaz et al., 2021) | 86.4 | 86.4 | 0.1 |
| **Logistic Regression** (Cook et al., 2016) | 81.7 | 81.7 | 0.2 |
| **LSTM**  (Zeberga et al., 2022) | 98.6 | 98.6 | 0.2 |
| **Random Forest classifier** (Malmasi et al., n.d.) | 72.9 | 72.9 | 0.3 |

*Table 1: Brief Overview of Mental Health Identification Algorithm Outcomes*

A bar plot comparing the accuracy levels of the models that were put into practice is shown in Figure 2. With its accuracy and F1-score of 93.28%, the LSTM+BERT combination clearly performs better than the other classifiers. Additionally, Figure 3's confusion matrix shows how well LSTM+BERT performs in various emotional categories for categorization

Figure 4 Bar-plot for the implemented models with accuracy value

### **4.1.2 Objective 2:** Using machine learning algorithms to detect linguistic patterns linked to certain mental health problems, such as depression and suicide ideation

Through an extensive literature review, various NLP techniques applied in mental health support were analyzed. The review encompassed studies on sentiment analysis, topic modeling, emotion detection, and language generation, among others. Key findings revealed the widespread use of NLP in analyzing social media data, clinical notes, and online forums to detect mental health issues such as depression, anxiety, and suicidal ideation. Moreover, the review highlighted the effectiveness of deep learning approaches, including LSTM, BERT, and transformer models, in capturing nuanced linguistic patterns indicative of mental health conditions. Additionally, the review identified gaps in existing literature, such as limited studies on specific demographic groups and cultural contexts, indicating the need for further research to address these limitations.

4.1.3 Objective 3: **To propose an integrated model combining NLP techniques with traditional mental health support systems to enhance accessibility and personalization of care.**

Based on the analysis of existing literature and emerging trends in NLP, several recommendations were proposed for integrating NLP into existing mental health support systems. Firstly, it was recommended to develop standardized protocols and guidelines for ethical data collection, storage, and analysis to ensure patient privacy and confidentiality. Secondly, there is a need to enhance interdisciplinary collaboration between NLP experts, mental health professionals, and domain experts to co-design NLP-based interventions tailored to diverse user needs. Additionally, the adoption of explainable AI techniques in NLP models was suggested to enhance transparency and interpretability, thereby fostering trust among users and clinicians. Moreover, the importance of continuous monitoring and evaluation of NLP-based interventions to assess their effectiveness, usability, and impact on patient outcomes was emphasized. Lastly, it was recommended to prioritize research efforts towards addressing cultural and linguistic diversity in mental health support systems, including the development of multilingual NLP models and culturally sensitive interventions to ensure inclusivity and accessibility for all populations.

## 4.2 DISCUSSION

The discussion covers each particular objective in detail and digs further into the results and implications of using Natural Language Processing (NLP) in mental health assistance.  
First, in terms of analysing NLP for early mental illness identification, the findings demonstrate the effectiveness of sophisticated NLP techniques in reliably recognizing emotional states from textual data, especially LSTM in conjunction with BERT. The enhanced efficacy of LSTM+BERT underscores the need of utilizing cutting-edge language models and deep learning architectures to accurately and promptly identify complex emotional expressions. By utilizing NLP, mental health practitioners may be able to identify inconspicuous indicators of psychological problems or distress in people, opening the door for preventative care and intervention techniques.

Going on to the advantages and disadvantages of present NLP applications, it is important to solve a number of issues even though the results show promise in terms of accuracy and predictive performance. A major obstacle is the possibility of bias in training data, which can lead to distorted or false predictions, especially when delicate mental health issues are involved. Concerns around data privacy and confidentiality also surface because NLP models might unintentionally collect and examine private information disclosed in textual data. Furthermore, the development of broadly applicable NLP models for mental health support is hindered by cultural variations and linguistic subtleties, underscoring the necessity of culturally sensitive and context-aware methodologies.

It becomes clear from talking about the difficulties and possibilities for NLP-based solutions that interdisciplinary cooperation and community involvement are crucial. A multidisciplinary strategy with feedback from NLP specialists, mental health professionals, ethicists, and community stakeholders is needed to address the issues that have been highlighted. Moreover, there are prospects for creating context-aware natural language processing (NLP) models that adjust to various socio-cultural settings, enhancing the usability and efficiency of mental health assistance programs. Innovative solutions that prioritize ethical considerations, respect cultural sensitivity, and enable people to seek and receive appropriate mental health support can be developed by encouraging collaboration and communication among stakeholders.

In conclusion, the results of the research suggest that even if issues like prejudice, privacy concerns, and cultural differences still exist, they can be resolved by taking proactive steps and working together. Through the strategic use of NLP's advantages and mitigation of its drawbacks, we may create a framework for mental health support in a variety of sociocultural situations that is more responsive, inclusive, and successful.

# CHAPTER FIVE: SUMMARY, RECOMMENDATIONS, CONCLUSION.

## 5.1 SUMMARY

The goal of this project was to evaluate existing NLP applications, identify potential and problems for implementation, and investigate the use of Natural Language Processing (NLP) in mental health assistance to detect early indicators of mental illness. The research involved a critical analysis of the research's significance for mental health support systems, a qualitative study of NLP algorithms and a thorough evaluation of the body of existing literature. The research revealed how advanced NLP approaches, especially LSTM in conjunction with BERT, may effectively identify emotional states from textual data, allowing for the early detection of mental health problems. But it also brought to light issues with cultural differences, privacy concerns, and bias in training data, highlighting the necessity of using NLP-based solutions with caution and ethics.

## 5.2 CONCLUSION

To sum everything up, the results of this study highlight how important NLP is to the transformation of mental health support systems because it makes individualized interventions and early diagnosis possible. Even though there are obstacles, such prejudice and privacy issues, these can be lessened by cooperation and ethical thought. The study highlights the value of community involvement and interdisciplinary collaboration in the creation of context-aware NLP models that consider the various sociocultural circumstances surrounding mental health.

## 5.3 RECOMMENDATIONS

Based on the findings, several recommendations are proposed for future research and implementation of NLP-based solutions in mental health support:

1. Continued research into improving NLP algorithms for detecting subtle signs of mental illness and adapting to diverse cultural contexts.
2. Development of guidelines and ethical frameworks for the responsible use of NLP in mental health support, ensuring privacy, confidentiality, and equity.
3. Collaboration between NLP experts, mental health professionals, ethicists, and community stakeholders to co-design and implement culturally sensitive NLP solutions.
4. Integration of user feedback and iterative refinement of NLP models to enhance accuracy, reliability, and user acceptance.
5. Exploration of novel NLP techniques, such as transfer learning and multi-modal analysis, to further enhance the effectiveness of mental health support systems.

## 5.4 FUTURE WORK

Future research could focus on:

1. Investigating the long-term effectiveness and impact of NLP-based interventions on mental health outcomes.
2. Exploring the integration of real-time data streams, such as social media feeds and wearable sensor data, into NLP models for continuous monitoring and intervention.
3. Examining the scalability and feasibility of deploying NLP-based solutions in low-resource settings and underserved communities.
4. Evaluating the potential of collaborative filtering and recommendation systems in personalizing mental health interventions based on individual preferences and needs.
5. Assessing the role of explainable AI techniques in enhancing transparency and trust in NLP-based mental health support systems.

In conclusion, the research focuses on the possible applications of NLP in mental health assistance and emphasizes the significance of interdisciplinary cooperation and ethical concerns in maximizing its advantages. Through the identification and resolution of specified obstacles and the utilization of favourable circumstances, NLP-based remedies possess the capacity to transform mental health services and enhance the well-being of people globally.

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# APPENDICES

