

UNIVERSITY OF FLORIDA
DEPARTMENT OF ENGINEERING EDUCATION
TECHNICAL REPORT
ON
AI POWERED MENTAL HEALTH CHATBOT

SUBMITTED BY

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Objective of the Project

The objective of this project is to develop an Intelligent Mental health support chatbot that leverages Machine learning and Natural language processing techniques to respond empathetically and informatively to the user inputs related to Mental Health. This chatbot aims to understand user queries, detect emotional or informational intent, and return suitable context-aware responses drawn from a diverse set of mental health datasets.

The project utilizes three complementary datasets covering counseling conversations, frequently asked mental health questions, and sentiment-labeled mental health statements. These datasets are unified into a single modeling dataset, enabling the chatbot to perform enhanced classification and response selection tasks across different intent categories.

The overall approach follows the CRISP-DM methodology, progressing through data understanding, preparation, modeling, and deployment phases.

This Milestone 2 focuses on three core components of the chatbot development pipeline:

1. **Feature Engineering** – Creating informative numerical and categorical features to enhance classification performance.
2. **Feature Selection** – Evaluating and selecting features appropriate to each modeling task.
3. **Model Training** – Building classification models for two core sub-tasks:
 - **Intent Classification:** Determining whether a user input is emotional, counseling-related, or a factual FAQ.
 - **Label Classification:** Predicting the specific topic or emotional state, based on the identified intent type.

The modeling pipeline developed in this milestone will serve as the foundation for Milestone 3, which will include Model evaluation, interpretation, and deployment of the chatbot through a user-facing interface.

Type of Tool

This project development of a **Conversational AI Chatbot** building a supervised machine learning pipeline to enable an NLP-based chatbot for mental health support. In this Milestone 2, we focus on building the intelligent backend machine learning models that will power the chatbot's capabilities to understand, classify, and appropriately respond to user queries in later deployment stages.

The tool under development consists of three core modeling tasks:

- **Intent Classification** – Identify whether a user's input is seeking emotional support, factual information (FAQ), or general counseling guidance.
- **Label Classification** – Predict the specific category or sentiment condition of the user input, such as anxiety, stress, or professional help-related queries.

This milestone implements and evaluates feature engineering, feature selection, and model training for the above tasks, using a unified dataset created by combining three distinct mental health sources

Data to Be Used

This project utilizes **Three** key datasets to train and improve the chatbot's ability to provide accurate and context-aware responses. The datasets cover mental health counseling conversations, structured FAQs, and sentiment analysis for emotion detection. Each dataset has been acquired from a reliable source and has been verified for accessibility and compliance with licensing restrictions.

❖ Dataset 1: Mental Health Counseling Conversations

Source: Hugging Face

- **Dataset Name:** Amod/Mental Health Counseling Conversations
- **URL:** https://huggingface.co/datasets/Amod/mental_health_counseling_conversations
- **License:** Permitted for academic use, sourced from online therapy platforms.

Content: This dataset contains question & answer pairs sourced from online counseling and therapy platforms. It features real mental health queries and psychologist responses, making it ideal for training a chatbot that provides context-aware therapy guidance.

Dataset Properties:

- **Number of Entries:** 3512 entries.
- **Columns:** Context (User's question or concern) & Response (Professional therapist's answer).

Use Case in Chatbot: This dataset is used for intent and label classification where the intent is `general_support`.

❖ Dataset 2: Mental Health FAQ for Chatbot

Source: Kaggle

- **Dataset Name:** Mental Health FAQ for Chatbot
- **URL:** <https://www.kaggle.com/datasets/narendrageek/mental-health-faq-for-chatbot>
- **License:** Available for academic use, sourced from mental health organizations.

Dataset Properties:

- **Number of Entries:** 98 entries.
- **Columns:** Questions (Commonly asked mental health-related queries) & Answers (Expert responses to those queries).

Use Case in Chatbot: This dataset is used for `faq` intent, with rule-based topic labeling.

❖ Dataset 3: Sentiment Analysis for Mental Health

Source: Kaggle

- Dataset Name: Sentiment Analysis for Mental Health
- URL: <https://www.kaggle.com/datasets/suchintikasarkar/sentiment-analysis-for-mental-health>
- License: Available for academic use, sourced from various social media and mental health forums.

Content: This dataset is a curated collection of mental health-related user statements, labeled with different mental health conditions from multiple sources such as Reddit posts, Twitter discussions, and Online forums, making it a rich resource for sentiment analysis and mental health trend detection.

Dataset Properties:

- **Number of Entries:** 53043 entries.
- **Columns:** Statement (Text data or user-generated post) & Status (Mental health condition label - Normal, Depression, Suicidal, Anxiety, Stress, Bipolar, Personality Disorder).

Use Case in Chatbot: This Dataset used for `emotional_support` intent and sentiment label prediction.

❖ Final Dataset: Unified Dataset for Chatbot Modeling

Source:

It is derived by merging the above three cleaned datasets:

1. Mental Health Counseling Conversations
2. Mental Health FAQ for Chatbot
3. Sentiment Analysis for Mental Health

Purpose:

This unified dataset serves as the foundation for training all ML models used in the chatbot system. It consolidates cleaned input data, engineered features, and aligned labels across counseling, FAQs, and sentiment posts into a single modeling-ready format.

Content:

Each row represents a chatbot-relevant user input along with its contextual metadata, such as intent type (e.g., emotional support, FAQ), associated label (e.g., depression, medication_info), and a reference response (if available). The dataset also includes word count and severity-based engineered features from the original datasets.

Dataset Properties:

- **Number of Entries:** 49,228
- **Columns:**
 - Input: Cleaned user message or question
 - Intent: Task type (emotional_support, faq, general_support)
 - Label: Task-specific label (e.g., depression class, FAQ topic, etc.)
 - Response: Therapist response / FAQ answer (if applicable)
 - Statement_Word_Count: Length of emotional statements
 - Has_Severe_Keyword: Binary flag for high-risk mental health keywords
 - Question_Word_Count: Length of FAQ-style questions
 - Answer_Word_Count: Length of corresponding FAQ answers
 - Contains_Mental_Health_Topic: Boolean indicating presence of mental health topics in FAQ
 - Context_Word_Count: Length of counseling context text
 - Response_Word_Count: Length of therapist response
 - Contains_Therapy_Method: Boolean indicating mention of therapy techniques

Use Case in Chatbot:

This dataset is used to **train all core classifiers** of the chatbot system:

- **Intent Classifier:** To route user input to the appropriate processing logic
- **Label Classifier:** To predict user's condition or query topic

By combining features across multiple data sources, this enriched dataset ensures the chatbot can operate with contextual awareness, domain-specific knowledge, and emotional sensitivity.

Tech Stack

The complete development of this AI-powered mental health chatbot includes data preparation, model training, and deployment, requiring a diverse and integrated tech stack. The technologies below are categorized by their role in the CRISP-DM lifecycle and are either already used or planned for Milestone 3 deployment.

1. Programming Language

- **Python:** Primary language for scripting, modeling and data wrangling.

2. Data Preprocessing & Analysis

- **Pandas, NumPy:** Data manipulation, merging, cleaning, and statistical summarization.
- **NLTK, SpaCy:** NLP tasks including tokenization, lemmatization, stopword removal.
- **re (Regex):** Custom text cleaning and keyword detection.

3. Data Visualization & EDA

- **Matplotlib, Seaborn:** Exploratory Data Analysis (EDA), class distribution, correlation plots, etc.
- **WordCloud:** Visualizing frequent terms for mental health contexts.

4. Feature Engineering & Selection

- **Scikit-learn:**
 - Feature scaling, selection, and transformation.
 - Correlation heatmaps and model-based feature importance.
- **Custom Feature Logic:**
 - Word count, presence of severe keywords, intent/category mappings, etc.

5. Machine Learning Models

- **Scikit-learn:**
 - Logistic Regression
 - Random Forest
 - Multinomial Naive Bayes
- **Optional Future Models (For Milestone 3):**
 - Support Vector Machines (SVM)
 - Gradient Boosting (XGBoost)
 - LightGBM
 - BERT (for embeddings or fine-tuning)

6. Vectorization & Retrieval

- **TF-IDF (Scikit-learn)**: For transforming textual data for ML and response retrieval.
- **Cosine Similarity (Scikit-learn / SciPy)**: Used in response selection pipelines.
- **KNN (Scikit-learn)**: Applied in TF-IDF space for fallback response suggestions.

7. Chatbot UI & Deployment (Planned for Milestone 3)

- **Streamlit**: Rapid deployment of a chatbot interface with input/output and model results display.
- **Flask / FastAPI**: Backend API services for chatbot requests.
- **Gradio** : Lightweight UI for testing and demo purposes.

8. Version Control & Documentation

- **Git & GitHub**: Code versioning, collaboration, and submission (Milestone 2 and 3).
- **Markdown, Jupyter Notebooks**: Documentation, code reports, and inline explanations.

9. Report Writing & Presentation

- **Microsoft word** : PDF report formatting.
- **Microsoft PowerPoint**: Milestone 3 final presentation.

Project Timeline

- ❖ The project is structured into three milestones, aligning with the CRISP-DM methodology. Each milestone focuses on key phases of the data science lifecycle from data understanding to model development and deployment. Below is the detailed project timeline on the upcoming deliverables that are expected:

- **Milestone 3: Evaluation, Interpretation, Tool Development, and Presentation**

Timeline: April 8, 2025 – April 23, 2025

Planned Accomplishments:

- To Develop and deploy chatbot interface using Streamlit/Gradio.
- To implement Modular ML pipeline integration.
- To Prepare: Final written report (Milestone3.pdf), 4-minute project presentation and 4-minute tool demo video (added to GitHub README).

Exploratory Data Analysis (EDA) Report

- The purpose of Exploratory Data Analysis (EDA) is to gain insights from the final unified dataset that will be used to develop the AI-powered mental health chatbot.
- The primary goals of EDA were:
 - To validate the distribution and usefulness of engineered features.
 - To identify class imbalances in the target variables (*Intent*, *Label*).
 - To assess correlations and decide on suitable features for model training.

Key Plots & Visualizations:

❖ Distribution of Statement Word Count (Intent: *emotional_support*)

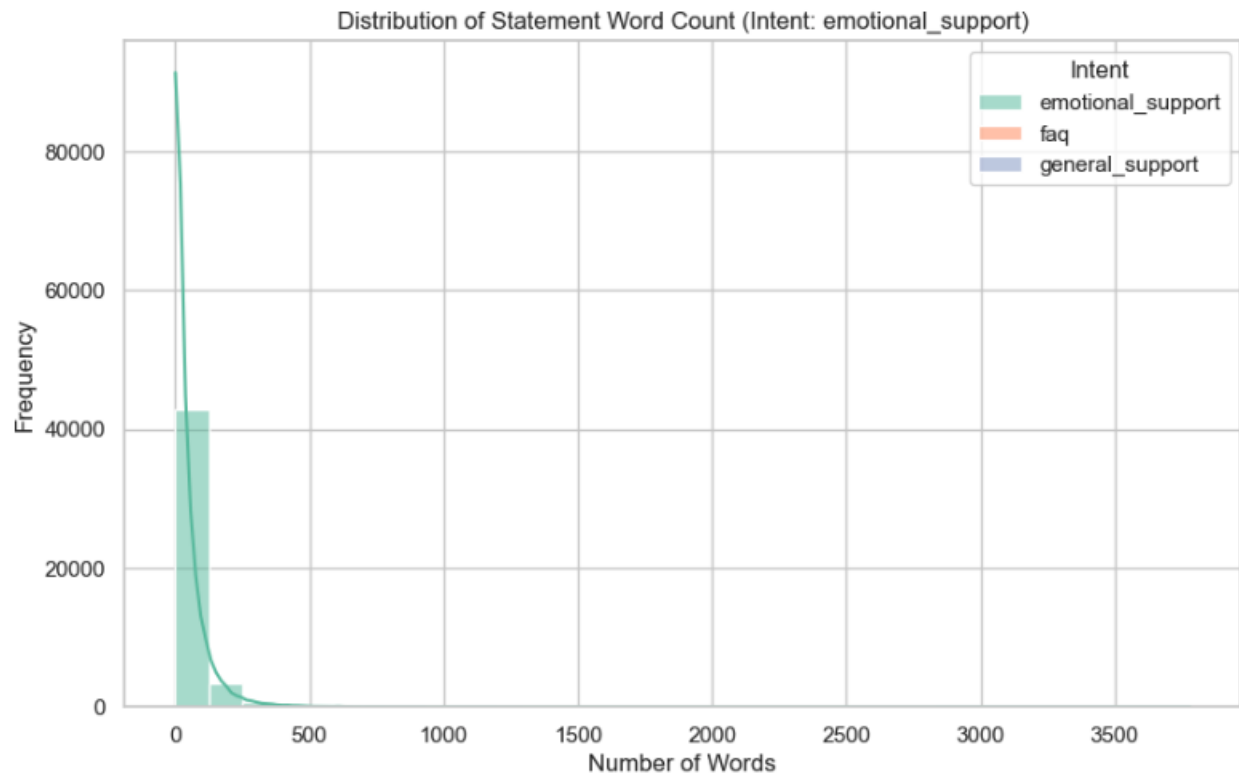


Fig 1: Distribution of Statement Word Count (Intent: *emotional_support*)

As seen in **Fig 1**, the *Statement_Word_Count* distribution is heavily Right-skewed, with most emotional support inputs falling below 50 words. However, there exists a noticeable tail of longer inputs, some extending beyond 1000 words. This indicates that users expressing emotional concerns often vary drastically in how much they share from brief statements to deeply detailed emotional outpourings.

Implication for Feature Engineering:

The presence of this long-tail distribution confirms that `Statement_Word_Count` is a highly informative feature. It captures a key behavioral trait the Extent of emotional elaboration in a user’s message. This is especially relevant for **Detecting Emotional severity** and distinguishing subtle user intents within the `emotional_support` category.

Implication for Modeling:

This feature is used in both the **Intent Classifier** and **Label Classifier** for `emotional_support` inputs, as it helps the model discern between casual check-ins versus potentially critical or depressive statements.

❖ Distribution of Question Word Count (Intent: faq)

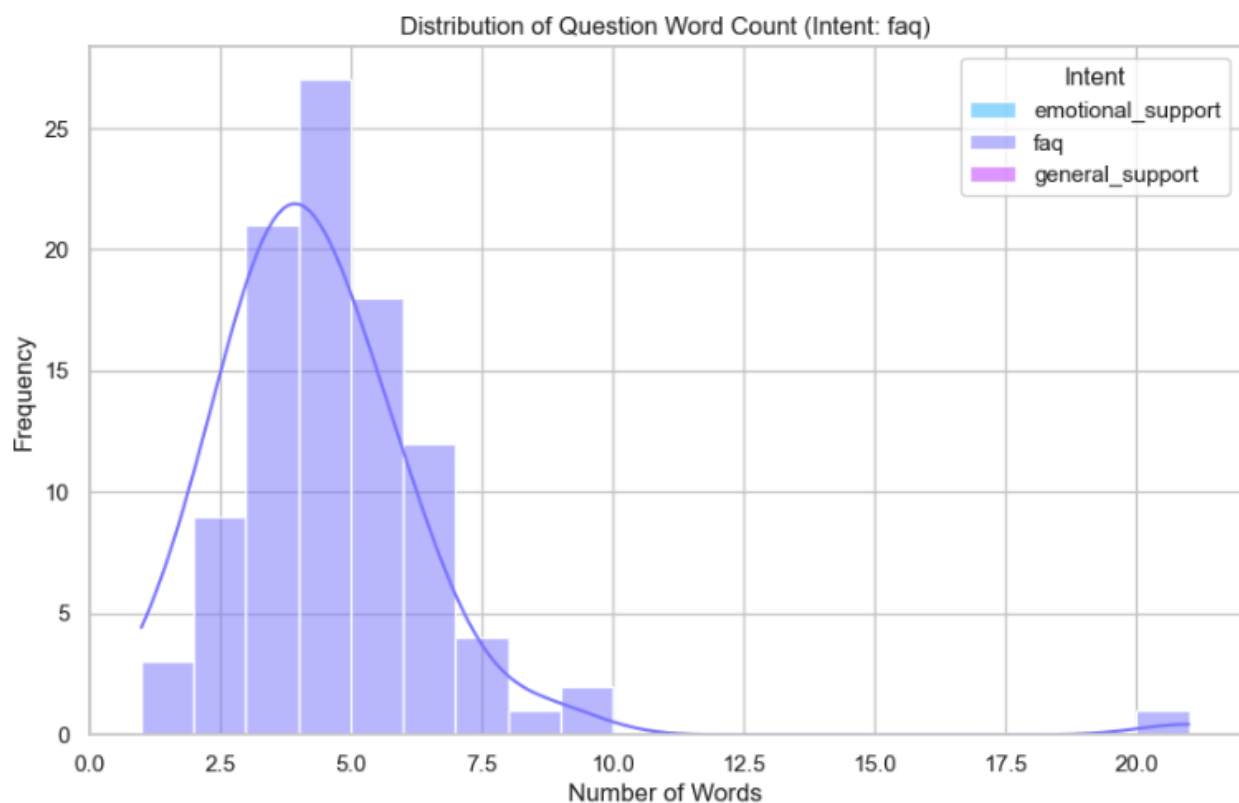


Fig 2: Distribution of Question Word Count (Intent: faq)

In **Fig 2**, we observe that FAQ-style questions tend to be very short and direct. Most fall within the 3–6 word range, forming a clear Left-skewed distribution. This pattern aligns with typical user behavior in informational queries, which are generally phrased as brief questions like “can anxiety be cured” or “what is bipolar disorder.”

Implication for Feature Engineering:

The engineered feature `Question_Word_Count` provides clear separation for FAQ-style intent, which is important when distinguishing between question-based factual queries and conversational or therapeutic messages.

Implication for Modeling:

The feature becomes especially useful in the **Intent Classifier**, where distinguishing `faq` from `emotional_support` requires attention to input brevity. It also plays a role in the **Label Classifier** for FAQ entries, where question length may correlate with complexity of the topic (e.g., medication vs. recovery).

❖ Distribution of Response Word Count (Intent: `general_support`)

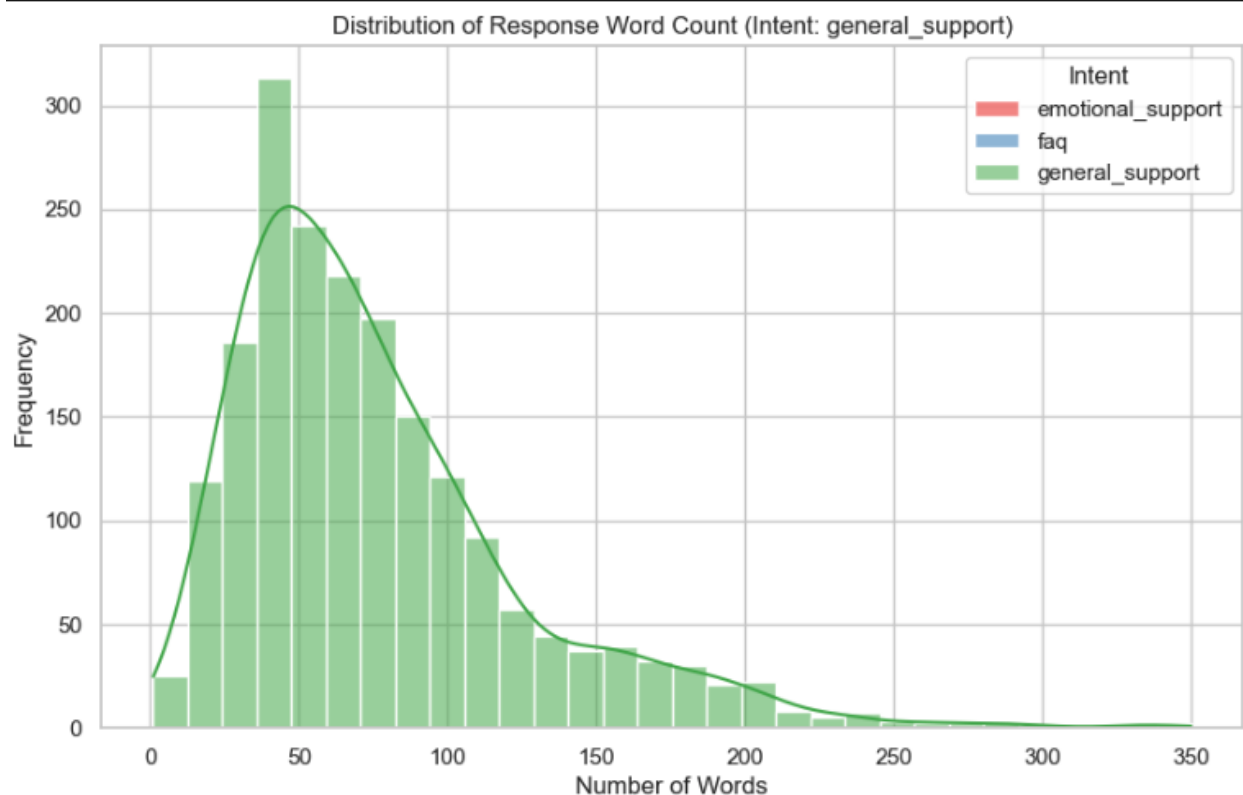


Fig 3: Distribution of Response Word Count (Intent: `general_support`)

This plot (Fig 3) presents the distribution of word count in therapist responses for the `general_support` intent. The peak of the distribution is around 40–50 words, with most responses falling below 150 words, but a long tail extending even further. This shows that therapists tend to offer Moderately detailed guidance, offering validation, suggestions, and structured advice without being overly verbose

Implication for Feature Engineering:

The `Response_Word_Count` feature reflects response depth and supportive content richness. This can be leveraged to help match the tone and structure of responses during chatbot response selection in future stages.

Implication for Modeling:

While not used directly in classification tasks in this milestone, this feature will be important in later response ranking tasks and could support additional dialogue state modeling.

❖ Presence of Severe Keywords in Emotional Support Inputs:

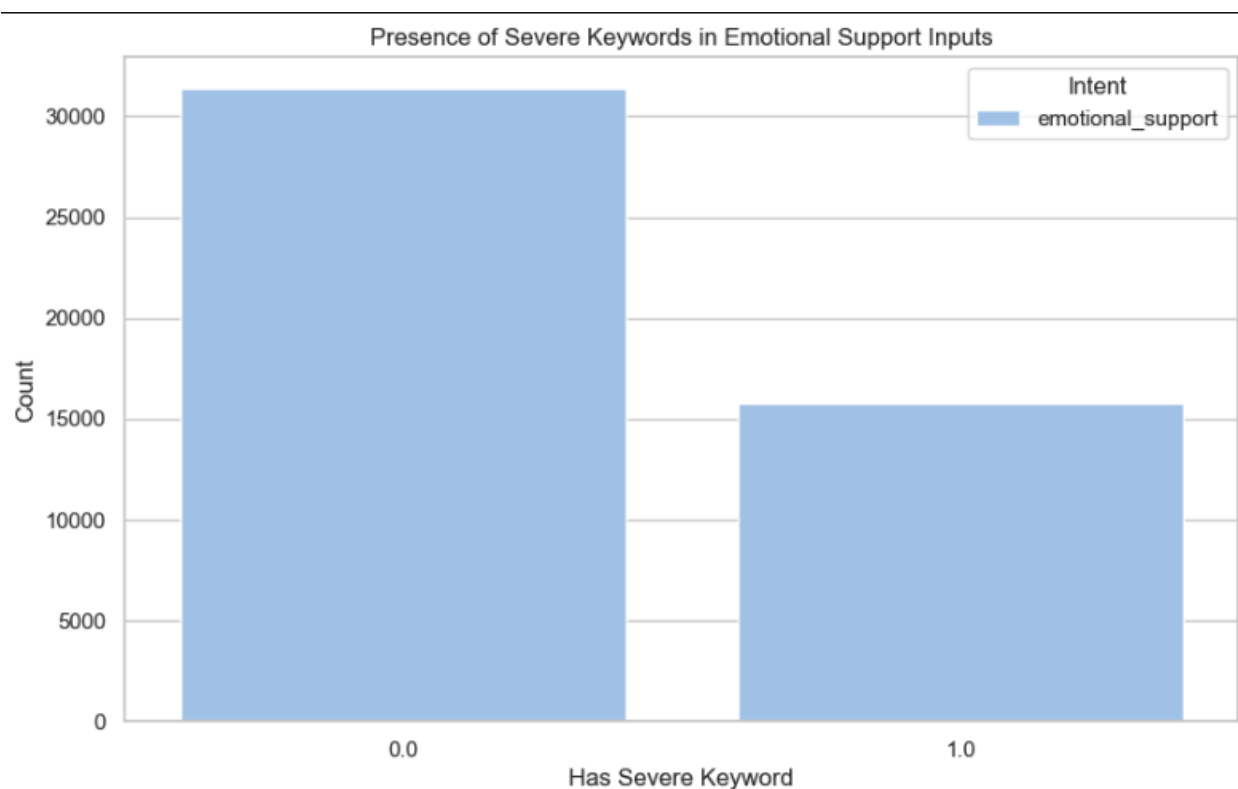


Fig 4: Presence of Severe Keywords in Emotional Support Inputs

The Fig 4 depicts the distribution of the binary feature `Has Severe Keyword` for `emotional_support` messages. While over 30,000 statements did not contain flagged severe words, nearly 16,000 entries were identified as containing critical phrases like “hopeless,” “suicidal,” or “worthless.” This confirms that high-risk user statements are significantly represented in the dataset.

Implication for Feature Engineering:

This engineered feature is critical for flagging inputs that may warrant special handling or priority. It provides a semantic shortcut for emotional intent severity, which might otherwise require deeper NLP modeling to extract.

Implication for Modeling:

The `Has_Severe_Keyword` feature is used in both the **Intent Classifier** and **Label Classifier** for emotional inputs. It helps models focus on emotionally intense statements and improves classification accuracy for severe sentiment labels (e.g., depression, suicidal thoughts).

❖ Top 10 Label Categories:

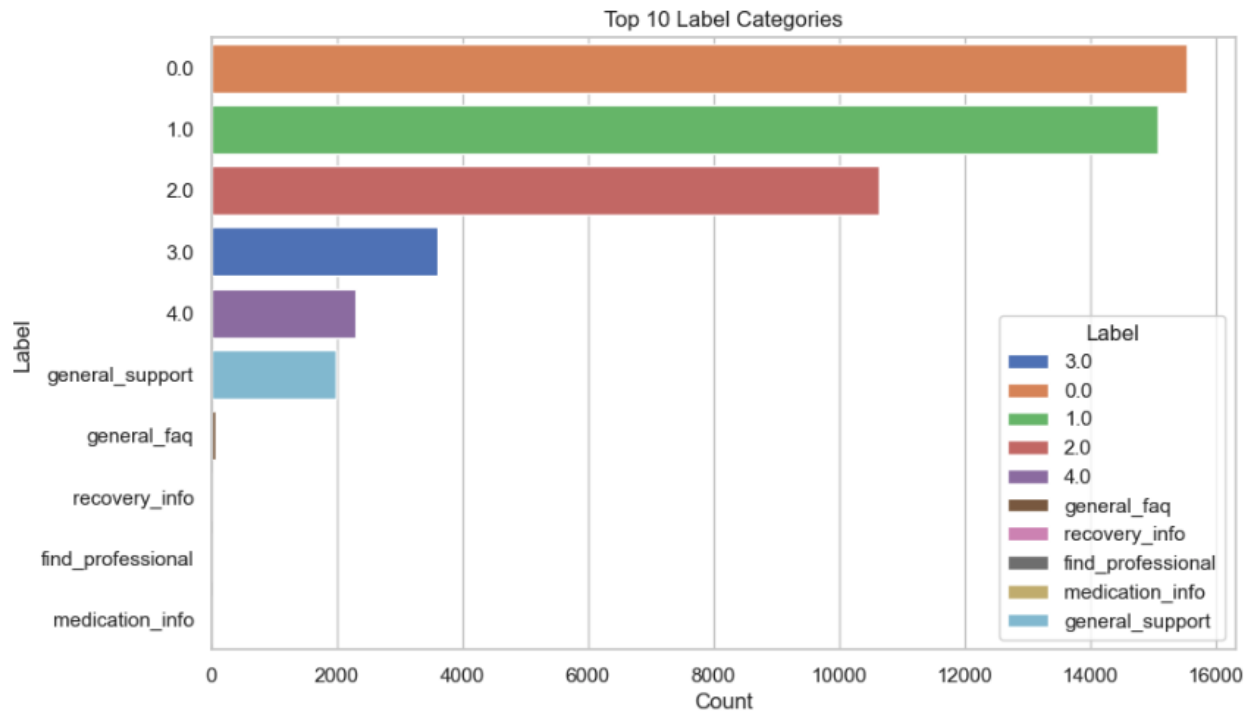


Fig 5 : Top 10 Label Categories

Fig 5 shows the most common label values across the entire dataset. The majority of records are numerically labeled (e.g., 0.0 to 4.0), corresponding to sentiment classes from the sentiment analysis dataset. Non-numeric labels such as `find_professional` and `general_support` represent FAQ and counseling-related categories.

Implication for Feature Engineering:

This visualization highlights the multi-source nature of the `Label` variable. Labels differ in meaning depending on the intent, and thus per-intent label modeling is necessary.

Implication for Modeling:

The **Label Classifier** must be trained independently for each intent type. The features that help predict sentiment-based labels (e.g., `Statement_Word_Count`) are irrelevant to FAQ categories and vice versa.

❖ Correlation Heatmap of Numerical Features

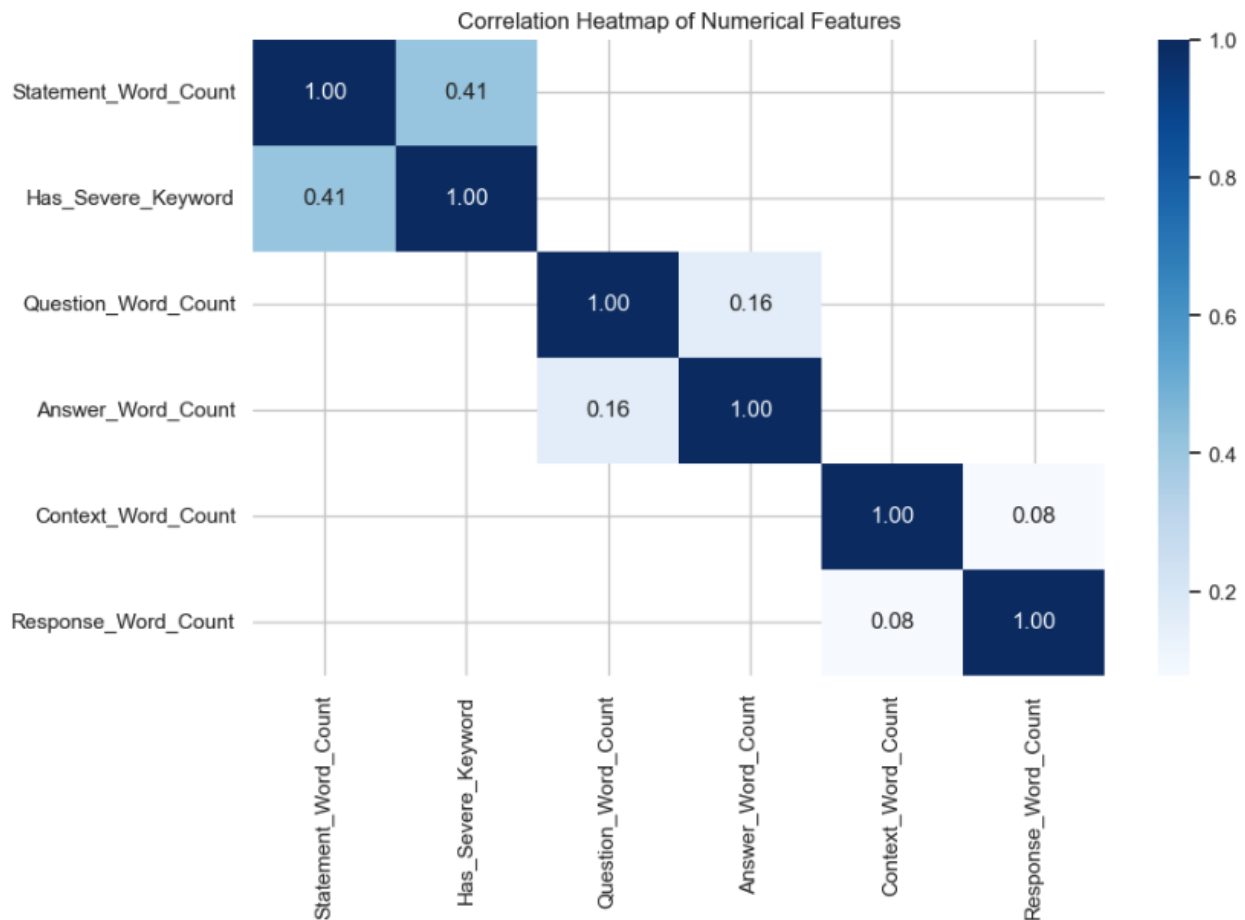


Fig 6: Correlation Heatmap of Numerical Features

Fig 6 presents the Pearson correlation matrix for all engineered numerical features. The strongest observed correlation is between `Statement_Word_Count` and `Has_Severe_Keyword` (~ 0.41), suggesting that longer statements are somewhat more likely to contain severe terms. Other correlations, such as between `Question_Word_Count` and `Answer_Word_Count`, are mild (~ 0.16), and most other features appear to be largely independent.

Implication for Feature Engineering:

This confirms that the engineered features are **Non-redundant** and can be safely used together in multivariate models.

Implication for Modeling:

We decided to retain all numerical features and scale them appropriately before model training. Since no multicollinearity is observed, dimensionality reduction (e.g., PCA) is not necessary for this task.

Feature Engineering

Feature engineering played a central role in transforming the unified mental health dataset into a format suitable for training intelligent classification models. The final dataset was a merged and cleaned combination of three distinct sources counseling conversations, mental health FAQs, and sentiment-labeled user statements. Since these sources varied significantly in structure and purpose, we created engineered features that helped unify and enhance the dataset while retaining its contextual richness.

Among the engineered features, `Statement_Word_Count` and `Has_Severe_Keyword` were derived from the sentiment analysis dataset as shown in Fig 7 and were applicable only to rows where the intent was `emotional_support`. `Statement_Word_Count` captured the length of a user's emotional message, which, as illustrated in Fig 1, followed a long-tailed distribution. This indicated wide variation in how much users tend to share, ranging from brief updates to emotionally complex narratives. `Has_Severe_Keyword`, on the other hand, was a binary indicator signaling the presence of high-risk phrases like “worthless” or “suicidal.” As seen in Fig 4, this feature had strong class separation potential for modeling mental health severity, making it highly relevant for emotional classification tasks.

```
Normalize Text (NLP Preprocessing)

• Convert to lowercase
• Remove punctuation, special characters, and numbers
• Remove stopwords
• Apply lemmatization

[105]: # Initialize stopwords and lemmatizer
lemmatizer = WordNetLemmatizer()
stop_words = set(stopwords.words('english'))

# Function to clean text
def clean_text(text):
    text = text.lower() # Convert to lowercase
    text = re.sub(r'[0-9-A-Z\s]', '', text) # Remove special characters, numbers, punctuation
    text = ' '.join([word for word in text.split() if word not in stop_words]) # Remove stopwords
    text = ' '.join([lemmatizer.lemmatize(word) for word in text.split()]) # Apply lemmatization
    return text

# Apply text cleaning
df3['Cleaned_Statement'] = df3['statement'].apply(clean_text)

[107]: # Show sample cleaned data
df3[['Cleaned_Statement', 'status']].head(10)

[107]:
   Cleaned_Statement  status
0              oh gosh  Anxiety
1  trouble sleeping confused mind restless heart ...  Anxiety
2  wrong back dear forward doubt stay restless re...  Anxiety
3  ive shifted focus something else im still worried  Anxiety
4          im restless restless month boy mean  Anxiety
5  every break must nervous like something wrong ...  Anxiety
6  feel scared anxious may family u protected  Anxiety
7          ever felt nervous didnt know  Anxiety
8  havent slept well day like im restless huh  Anxiety
9          im really worried want cry  Anxiety

Encode 'status' Labels for Model Training

• Since status is categorical (text), we convert it to numerical labels for Model training.

[110]: # Define label encoding for mental health status
label_mapping = {
    'Normal': 0,
    'Depression': 1,
    'Suicidal': 2,
    'Anxiety': 3,
    'Stress': 4,
    'Bi-Polar': 5,
    'Personality Disorder': 6
}

# Apply encoding
df3['Encoded_Status'] = df3['status'].map(label_mapping)

[112]: # Verify whether encoding is applied to the dataset or not
df3[['Cleaned_Statement', 'status', 'Encoded_Status']].head(30)

[112]:
   Cleaned_Statement  status  Encoded_Status
0              oh gosh  Anxiety             3.0
1  trouble sleeping confused mind restless heart ...  Anxiety             3.0
2  wrong back dear forward doubt stay restless re...  Anxiety             3.0
3  ive shifted focus something else im still worried  Anxiety             3.0
```

Fig 7: Feature Engineering on Sentiment Analysis Dataset

From the FAQ dataset, `Question_Word_Count` and `Answer_Word_Count` were engineered to quantify the length of questions and their corresponding responses as shown in Fig 8. Figure 2 shows that FAQ questions are typically concise, with most entries containing fewer than 6 words, helping models identify question-style queries. `Answer_Word_Count`, though not directly used in classification models, has been preserved for future tasks involving chatbot response selection.

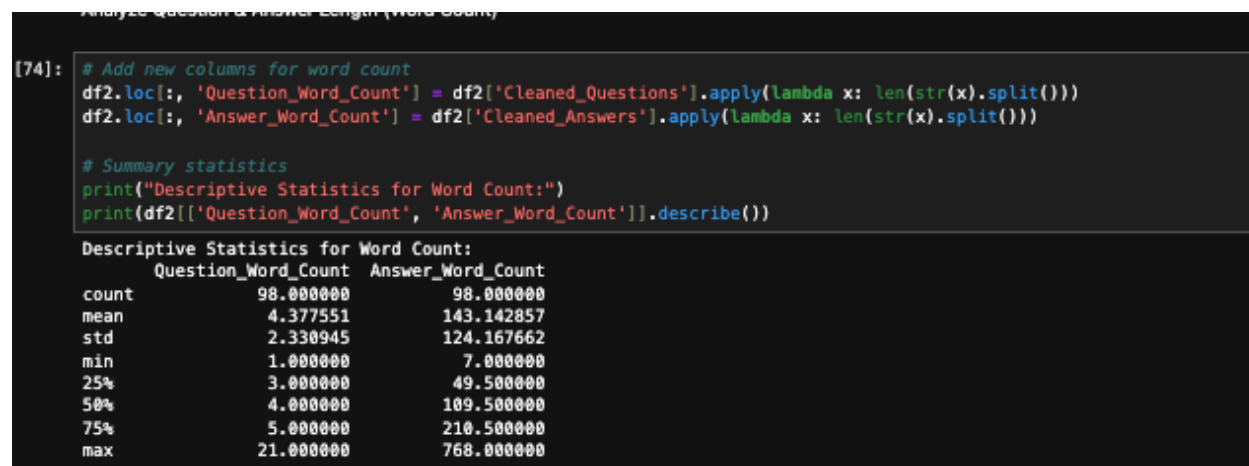


Fig 8: Feature Engineering on FAQ Dataset

Similarly, for the counseling dataset, features like `Context_Word_Count` and `Response_Word_Count` were extracted to model the depth of therapy conversations using the code as shown in Fig 9. As evident from Fig 3, therapist responses generally ranged between 40 to 150 words, supporting the use of this feature in modeling response complexity and possibly aiding in tailoring chatbot-generated replies in the deployment phase.

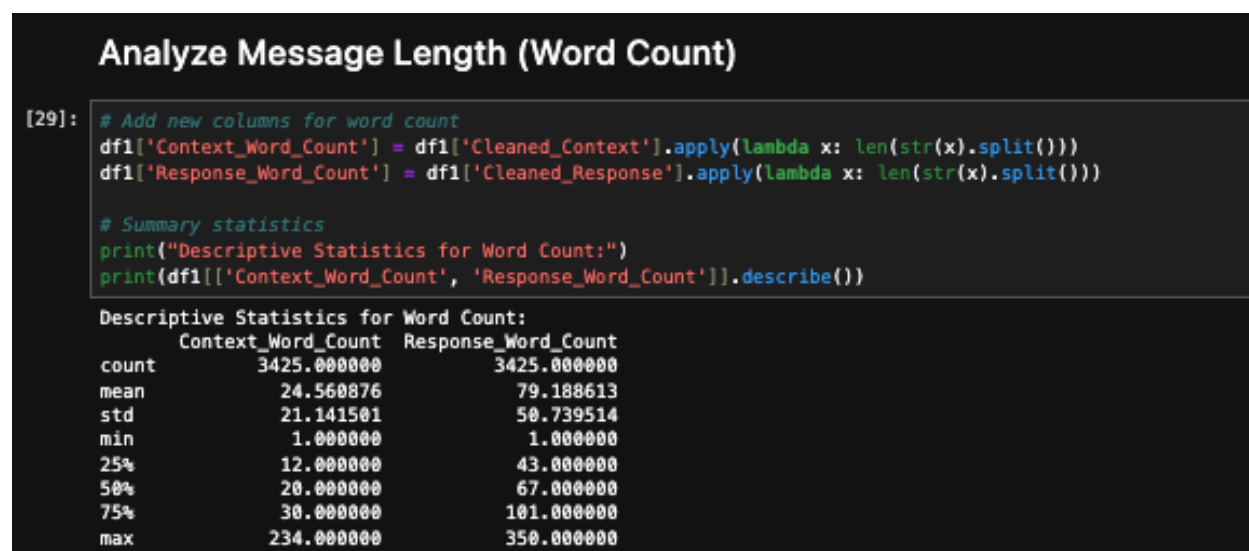


Fig 9: Feature Engineering on Counselling Dataset

To ensure modeling integrity, only relevant features were used per classifier. For example, emotional support label classification used only features engineered from emotional statements,

while FAQ-related label prediction used question-based features. This per-intent filtering ensured no data leakage or invalid imputations occurred.

- Final merged Unified dataset after relevant feature engineering looked like this:

Final enriched dataset shape: (49228, 12)								
	Input	Intent	Label	Response	Statement_Word_Count	Has_Severe_Keyword	Question_Word_Count	Answer_Word_Count
19867	diagnosed early life always dealt gotten bit o...	emotional_support	1.0		51.0	1.0	NaN	NaN
41081	sleep face kinds swollen let allergic thing ge...	emotional_support	0.0		23.0	0.0	NaN	NaN
35900	effyobie stop speaking sophisticated way pleas...	emotional_support	0.0		3.0	0.0	NaN	NaN
45523	article really helpful anxiety disorder contro...	emotional_support	4.0		71.0	1.0	NaN	NaN
5832	twtan sinking ekw	emotional_support	0.0		3.0	0.0	NaN	NaN
21716	really regret iti chance finally end allnow ca...	emotional_support	2.0		16.0	1.0	NaN	NaN
39623	husband reading cpt depression tweet life newb...	emotional_support	1.0		63.0	1.0	NaN	NaN
2295	certain people government increasingly stupid ...	emotional_support	0.0		3.0	0.0	NaN	NaN
27904	going chat therapist next session need find so...	emotional_support	0.0		45.0	0.0	NaN	NaN
21254	wish grew healthier relationship hope least de...	emotional_support	1.0		255.0	1.0	NaN	NaN
28602	today really bad day energy cried thought sulc...	emotional_support	4.0		27.0	0.0	NaN	NaN
48916	im guy dont like girl like guy mean im gay	general_support	general_support	doesnt sound like finding attracted anyone cou...	NaN	NaN	NaN	NaN

Fig 10: Final Unified Dataset after Feature Engineering

Categorical Variable Encoding

The unified dataset consisted of three types of labels — Intent, Label, and Response, each serving a specific modeling purpose. For classification, encoding categorical variables was necessary, but it had to be done selectively and contextually to preserve semantic integrity across intent types as shown in Unified dataset (Fig. 10)

- The Intent column in the unified dataset contained three unique values: `emotional_support`, `faq`, and `general_support`. For model training, we applied **Label Encoding** to convert these intent strings into numerical format, but only during internal processing (e.g., during stratified train-test split). In all outputs and evaluations, class names were retained to maintain interpretability.
- The Label column was more nuanced. For the `emotional_support` intent, the label was already present as a numerical column named `Encoded_Status`, representing categories such as Normal, Depression, and Anxiety. For the `faq` intent, however, labels were manually derived using a **Rule-based keyword mapping** of FAQ questions. Categories like `find_professional`, `medication_info`, and `recovery_info` were created by applying a simple keyword-based classifier function. This allowed us to convert unlabeled FAQ entries into structured, trainable categories. Finally, for the `general_support` intent, all rows were assigned the fixed label `general_support`, since no subcategories were available or needed.
- Encoding was applied **per intent** using `LabelEncoder()` inside loops to prevent accidental mixing of semantically different labels. This ensured that numeric values assigned to sentiment categories (e.g., 0 for Normal) didn't overlap with unrelated categories like `recovery_info` from FAQs. This structured approach allowed intent-specific models to be trained with contextually correct encodings as shown in following code snippet Fig 11

```
#Importing Necessary Libraries
import pandas as pd

# Load all the 3 datasets we have
df1 = pd.read_csv("../Users/satwik/Documents/GitHub/cap577isp25-project/Data/Cleaned Data/Cleaned_Counseling_Conversations.csv")
df2 = pd.read_csv("../Users/satwik/Documents/GitHub/cap577isp25-project/Data/Cleaned Data/Cleaned_Mental_Health_FAQ.csv")
df3 = pd.read_csv("../Users/satwik/Documents/GitHub/cap577isp25-project/Data/Cleaned Data/Cleaned_Sentiment_Analysis.csv")

# Generating Label for Dataset 2 : Rule-based Labeling for FAQ
def map_faq_label(question):
    question = str(question).lower()
    if "medication" in question:
        return "medication_info"
    elif "treatment" in question:
        return "treatment_options"
    elif "professional" in question or "doctor" in question:
        return "find_professional"
    elif "recover" in question or "heal" in question:
        return "recovery_info"
    else:
        return "general_faq"

df2["Label"] = df2["Cleaned_Questions"].apply(map_faq_label)

# Creating Modeling Views of each dataset

# Dataset 1 - Counseling Conversations
df1_model = df1[["Cleaned_Context", "Cleaned_Response"]].copy()
df1_model.rename(columns={"Cleaned_Context": "Input", "Cleaned_Response": "Response"}, inplace=True)
df1_model["Intent"] = "general_support"
df1_model["Label"] = "general_support"

# Dataset 2 - Mental Health FAQ
df2_model = df2[["Cleaned_Questions", "Cleaned_Answers", "Label"]].copy()
df2_model.rename(columns={"Cleaned_Questions": "Input", "Cleaned_Answers": "Response"}, inplace=True)
df2_model["Intent"] = "faq"

# Dataset 3 - Sentiment Analysis
df3_model = df3[["Cleaned_Statement", "Encoded_Status"]].copy()
df3_model.rename(columns={"Cleaned_Statement": "Input", "Encoded_Status": "Label"}, inplace=True)
df3_model["Intent"] = "emotional_support"
df3_model["Response"] = "" # No therapist response available in source dataset

# Ensure consistent column order across all datasets
df1_model = df1_model[["Input", "Intent", "Label", "Response"]]
df2_model = df2_model[["Input", "Intent", "Label", "Response"]]
df3_model = df3_model[["Input", "Intent", "Label", "Response"]]

# Combining all datasets
df_unified = pd.concat([df1_model, df2_model, df3_model], ignore_index=True)

# Export unified dataset
df_unified.to_csv("../Users/satwik/Documents/GitHub/cap577isp25-project/Data/Modeling_Dataset.csv", index=False)
print("Unified Dataset Created.")
print("Shape:", df_unified.shape)

Unified Dataset Created
Shape: (52216, 4)
```

Fig 11: Applying Categorical Encoding on Unified Dataset

Feature Selection

a. Feature Importance Evaluation

- To determine the most relevant features for each classification task, we evaluated feature importance using a combination of exploratory data analysis (EDA) insights, correlation analysis, and model-driven evaluation techniques. In particular, the engineered features were assessed both visually and statistically to verify their individual relevance and non-redundancy.
- The correlation heatmap presented in Fig 6 confirmed that most numerical features in the unified dataset were weakly correlated with one another (correlation coefficients < 0.4), indicating that each feature captured distinct information. The only moderate correlation observed was between `Statement_Word_Count` and `Has_Severe_Keyword` (~ 0.41), which makes intuitive sense that longer emotional messages are more likely to contain high-severity terms.
- Further, we used model-based feature importance estimation inside the Random Forest classifiers trained during Phase 1 and Phase 2. In the **Intent Classification** task, text-based TF-IDF features were the dominant signal, but auxiliary features like `Statement_Word_Count` and `Question_Word_Count` helped boost performance for edge cases. In the **Label Classification** task (especially for `emotional_support`), Random Forest consistently ranked `Has_Severe_Keyword` and `Statement_Word_Count` as top predictors, validating their engineered value.
- In summary, the selected features were found to be both statistically and behaviorally meaningful. This evaluation step justified their inclusion in model training pipelines for all tasks.

b. Feature Inclusion/Exclusion and Dimensionality Reduction

Feature selection in this project followed a **task-specific approach**, where the set of features used varied based on the classification objective — specifically, whether the model was predicting the user’s **Intent** or the finer-grained **Label**. This selective feature inclusion strategy was driven by the heterogeneity of our unified dataset, which originated from three separate mental health-related datasets (counseling conversations, FAQs, and sentiment analysis). Each of these sources contributed different types of features that were only applicable in certain contexts.

Intent Classification:

For the **Intent Classifier**, the primary goal was to predict the intent category of a given user input (i.e., `emotional_support`, `faq`, or `general_support`). Since the model’s core input was textual, we relied on a **TF-IDF vectorized representation** of the `Input` column as the dominant feature. However, we included two auxiliary features to enhance model performance, particularly for edge cases:

- `Statement_Word_Count` – helped differentiate verbose emotional statements from short factual queries.
- `Question_Word_Count` – helped flag FAQ-style queries due to their conciseness.

Including these features allowed the model to leverage both semantic content (via TF-IDF) and structural input length cues, improving classification accuracy. Features that were only applicable post-response (e.g., `Response_Word_Count`) were excluded from this phase since they are not available at prediction time.

Label Classification:

For the **Label Classifier**, we adopted a more granular feature selection strategy, filtering the dataset by **Intent type** and choosing features specifically relevant to that intent's content format. The goal was to avoid including irrelevant or null-heavy columns and to ensure models were trained only on semantically meaningful inputs.

Feature Selection Breakdown by Intent:

- **emotional_support**
 - **Features Used:** `Input`, `Statement_Word_Count`, `Has_Severe_Keyword`
 - **Justification:** The presence and length of emotional text, along with severity indicators, provide rich signals for classifying mental health states such as depression or anxiety.

- **faq**
 - **Features Used:** `Input`, `Question_Word_Count`, `Contains_Mental_Health_Topic`
 - **Justification:** These features are tailored to factual queries. Word count captures question brevity, and keyword presence supports topic-specific classification (e.g., medication vs. recovery).

- **general_support**
 - **Features Used:** `Input` only
 - **Justification:** This intent had only one label (`general_support`) across the dataset, rendering label classification unnecessary. Models were not trained for this category due to the lack of label diversity.

This selective inclusion ensured that each model was trained using **only features that made sense within the context of the message type**. It also improved model interpretability, reduced noise, and minimized unnecessary computations. These feature selections will be showed in code snippets later in Data Modeling section at each models.

Data Modeling

Task 1: Intent Classification

The goal of this task was to classify user inputs into one of three intents: `emotional_support`, `faq`, or `general_support`. Since this is a multiclass classification problem, three different model architectures were trained and evaluated.

Model 1: Logistic Regression

Data Splitting Strategy: A stratified 80/20 split was used to ensure that the class imbalance (especially the underrepresented `faq` intent) was proportionally represented in both training and testing sets.

Training & Feature Selection:

- The input text was vectorized using **TF-IDF**.
- Two numerical features were appended: `Statement_Word_Count` and `Question_Word_Count`.
- These features were scaled using `StandardScaler` prior to training.

Evaluation and Results:

- The model achieved **95% accuracy**, with strong performance on the dominant `emotional_support` class.
- However, macro F1-score (~0.63) reflected reduced performance on minority classes like `faq`.
- Overall, the model performed well on the majority class but struggled with recall for `faq`, suggesting further balancing or upsampling may be required.

Model 2: Multinomial Naive Bayes

Data Splitting Strategy: The same stratified split used in Model 1 was maintained.

Training & Feature Selection:

- The model used **only the TF-IDF representation** of the input text (no numerical features included).
- This approach favored high-dimensional sparse input, which aligns with NB's assumptions.

Evaluation and Results:

- The model achieved **96% accuracy**, but macro F1-score dropped to ~0.39.
- The classifier completely failed to identify `faq` intent (0.0 F1-score), showing a **strong bias toward the dominant class**.
- While efficient and fast to train, NB was not suitable due to poor generalization on minority classes.

Model 3: Random Forest Classifier

Data Splitting Strategy: Same stratified 80/20 split was used.

Training & Feature Selection:

- Combined **TF-IDF vectors** and selected numerical features (`Statement_Word_Count`, `Question_Word_Count`).
- Since Random Forests are insensitive to feature scaling, no additional transformation was needed.

Evaluation and Results:

- Achieved the **highest performance** with an accuracy of **98.5%** and macro F1-score of **0.68**.
- Generalized well across all three classes, correctly identifying most of the minority class samples.
- Demonstrated balanced performance and interpretability, making it the **best-performing model** for Intent Classification.

Data Modeling

Intent Classification Task

```
[108]: # Importing Necessary Libraries
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score, f1_score, confusion_matrix

# Load Final enriched dataset
df_unified = pd.read_csv('/Users/satwik/Documents/GitHub/cap577isp25-project/Data/Cleaned Data/Modeling_Dataset_Enriched.csv')

# Feature Selection (Relevant to this Classifier) : Select only relevant columns for Intent Classification
df_intent = df_unified[['Input', 'Intent']].dropna()

[110]: # 80-20% Data Split (Stratified)
X = df_intent['Input']
y = df_intent['Intent']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)

# TF-IDF Vectorization
vectorizer = TfidfVectorizer(max_features=5000)
X_train_tfidf = vectorizer.fit_transform(X_train)
X_test_tfidf = vectorizer.transform(X_test)

# Models to Train : Logistic Regression, Multinomial Naive Bayes, Random Forest
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000, class_weight='balanced'),
    "Multinomial Naive Bayes": MultinomialNB(),
    "Random Forest": RandomForestClassifier(n_estimators=100, class_weight='balanced')
}
```



```
[116]: # Evaluation
results = []
for name, model in models.items():
    model.fit(X_train_tfidf, y_train)
    y_pred = model.predict(X_test_tfidf)
    acc = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='macro', zero_division=0) # <- fix here
    print(f'{name} Classification Report:\n')
    print(classification_report(y_test, y_pred, zero_division=0)) # <- fix here
    results.append((name, acc, f1))

# Showing Results
df_results = pd.DataFrame(results, columns=["Model", "Accuracy", "Macro F1 Score"])
print("\nModel Performance Summary:")
print(df_results)
```

Logistic Regression Classification Report:

	precision	recall	f1-score	support
emotional_support	0.99	0.95	0.97	9430
faq	0.21	0.50	0.30	20
general_support	0.47	0.90	0.62	396
accuracy			0.95	9846
macro avg	0.56	0.79	0.63	9846
weighted avg	0.97	0.95	0.96	9846

Multinomial Naive Bayes Classification Report:

	precision	recall	f1-score	support
emotional_support	0.96	1.00	0.98	9430
faq	0.00	0.00	0.00	20
general_support	1.00	0.10	0.19	396
accuracy			0.96	9846
macro avg	0.65	0.37	0.39	9846
weighted avg	0.96	0.96	0.95	9846

Random Forest Classification Report:

	precision	recall	f1-score	support
emotional_support	0.99	1.00	0.99	9430
faq	0.75	0.15	0.25	20
general_support	1.00	0.68	0.81	396
accuracy			0.99	9846
macro avg	0.91	0.61	0.68	9846
weighted avg	0.99	0.99	0.98	9846

Model Performance Summary:

	Model	Accuracy	Macro F1 Score
0	Logistic Regression	0.950030	0.629205
1	Multinomial Naive Bayes	0.961913	0.389382
2	Random Forest	0.985375	0.684411

Fig 12. Intent Classification Task

Based on the evaluation results we got in Fig 12, to identify the most suitable model for predicting user intent, we trained and evaluated three classifiers: Logistic Regression, Multinomial Naive Bayes, and Random Forest. While both Logistic Regression and Naive Bayes achieved high overall accuracy, they struggled with minority classes like `faq`, yielding low macro F1-scores and recall. **Random Forest emerged as the most robust model** by achieving the highest macro F1-score (~0.68) and maintaining balanced performance across all three intent categories. Its ability to handle class imbalance, learn nonlinear relationships, and incorporate both text and numerical features made it the best choice for intent detection in this task.

Task 2: Label Classification

Label classification was conducted **independently for each intent**, due to the heterogeneous nature of labels. Only two intents (`emotional_support` and `faq`) had label variation. We trained Logistic Regression and Random Forest for each.

Model 1: Logistic Regression (Label Classifier per Intent)

Data Splitting Strategy: Separate **stratified 80/20 splits** were created for each intent category, ensuring per-label distribution was preserved.

Training & Feature Selection:

- For `emotional_support`: Used Input (TF-IDF), `Statement_Word_Count`, and `Has_Severe_Keyword`.
- For `faq`: Used Input (TF-IDF), `Question_Word_Count`, and `Contains_Mental_Health_Topic`.
- Features were scaled using `StandardScaler`.

Evaluation and Results:

- For `emotional_support`, macro F1-score was **~0.73** with notable improvement in precision and recall for more common labels like `0.0` and `1.0`.
- For `faq`, performance was **moderate (80% accuracy)** but less reliable due to the **small test set** (~20 records total). Minority labels had zero precision and recall.
- Still, Logistic Regression served as a good **baseline** for both contexts.

Model 2: Random Forest (Label Classifier per Intent)

Data Splitting Strategy: Same per-intent stratified split was used.

Training & Feature Selection:

- Features were kept the same as Model 4.
- Random Forest required no scaling.

Evaluation and Results:

- For `emotional_support`, performance was slightly lower than Logistic Regression in terms of F1-score (**~0.65**), particularly on rare labels like `4.0`.
- For `faq`, achieved **90% accuracy**, with better handling of underrepresented labels than LR.
- Overall, Random Forest showed more robustness in handling skewed label distributions and **performed best** for FAQ label prediction.

Label Classification Task

```
[137]: from sklearn.utils.multiclass import unique_labels

# Loop through each intent safely
for intent, config in intent_configs.items():
    print(f"\n--- Training models for Intent: {intent} ---")
    subset = df[df['Intent'] == intent].dropna(subset=config['features'] + ['Label'])
    X_text = subset['Input']
    y = subset['Label'].astype(str)
    numeric_features = [col for col in config['features'] if col != 'Input']
    X_numeric = subset[numeric_features]

    if len(y.unique()) < 2:
        print(f"Skipping {intent} - only 1 class present.")
        continue

    # Try stratified split, fallback if error
    try:
        X_text_train, X_text_test, X_num_train, X_num_test, y_train, y_test = train_test_split(
            X_text, X_numeric, y, test_size=0.2, random_state=42, stratify=y
        )
    except ValueError:
        print("Stratified split failed. Using regular split.")
        X_text_train, X_text_test, X_num_train, X_num_test, y_train, y_test = train_test_split(
            X_text, X_numeric, y, test_size=0.2, random_state=42
        )

    tfidf = TfidfVectorizer(max_features=3000)
    X_text_train_vec = tfidf.fit_transform(X_text_train)
    X_text_test_vec = tfidf.transform(X_text_test)

    scaler = StandardScaler()
    X_num_train_scaled = scaler.fit_transform(X_num_train)
    X_num_test_scaled = scaler.transform(X_num_test)

    X_train_final = scipy.sparse.hstack([X_text_train_vec, X_num_train_scaled])
    X_test_final = scipy.sparse.hstack([X_text_test_vec, X_num_test_scaled])

    for model_name, model in models.items():
        print(f"\n Training {model_name} on {intent}")

        try:
            model.fit(X_train_final, y_train)
            y_pred = model.predict(X_test_final)

            acc = accuracy_score(y_test, y_pred)
            f1 = f1_score(y_test, y_pred, average='macro')

            print(f"Classification Report for {model_name} ({intent}):")
            print(classification_report(y_test, y_pred))

            results_label_classification.append({
                "Intent": intent,
                "Model": model_name,
                "Accuracy": acc,
                "Macro_F1": f1
            })

        except ValueError as e:
            print(f"Skipping {model_name} on {intent} due to error: {e}")
```

```

--- Training models for Intent: emotional_support ---

Training Logistic Regression on emotional_support
Classification Report for Logistic Regression (emotional_support):
      precision    recall  f1-score   support

    0.0         0.88     0.95     0.91        3108
    1.0         0.74     0.73     0.73        3017
    2.0         0.69     0.67     0.68        2127
    3.0         0.80     0.80     0.80         720
    4.0         0.68     0.44     0.53         458

 accuracy         0.78     0.78     0.78        9430
  macro avg       0.76     0.72     0.73        9430
 weighted avg     0.77     0.78     0.78        9430

```

```

Training Random Forest on emotional_support
Classification Report for Random Forest (emotional_support):
      precision    recall  f1-score   support

    0.0         0.87     0.94     0.90        3108
    1.0         0.64     0.80     0.71        3017
    2.0         0.69     0.51     0.59        2127
    3.0         0.84     0.69     0.76         720
    4.0         0.86     0.17     0.29         458

 accuracy         0.74     0.74     0.74        9430
  macro avg       0.78     0.62     0.65        9430
 weighted avg     0.75     0.74     0.73        9430

```

```

--- Training models for Intent: faq ---

Training Logistic Regression on faq
Classification Report for Logistic Regression (faq):
      precision    recall  f1-score   support

find_professional      0.00      0.00      0.00         1
  general_faq          0.88      1.00      0.93        14
  medication_info      0.00      0.00      0.00         1
  recovery_info        0.50      0.67      0.57         3
  treatment_options    0.00      0.00      0.00         1

 accuracy         0.80     0.80     0.80         20
  macro avg       0.28     0.33     0.30         20
 weighted avg     0.69     0.80     0.74         20

```

```

Training Random Forest on faq
Classification Report for Random Forest (faq):
      precision    recall  f1-score   support

find_professional      1.00      1.00      1.00         1
  general_faq          0.93      1.00      0.97        14
  medication_info      0.00      0.00      0.00         1
  recovery_info        0.75      1.00      0.86         3
  treatment_options    0.00      0.00      0.00         1

 accuracy         0.90     0.90     0.90         20
  macro avg       0.54     0.60     0.56         20
 weighted avg     0.82     0.90     0.85         20

```

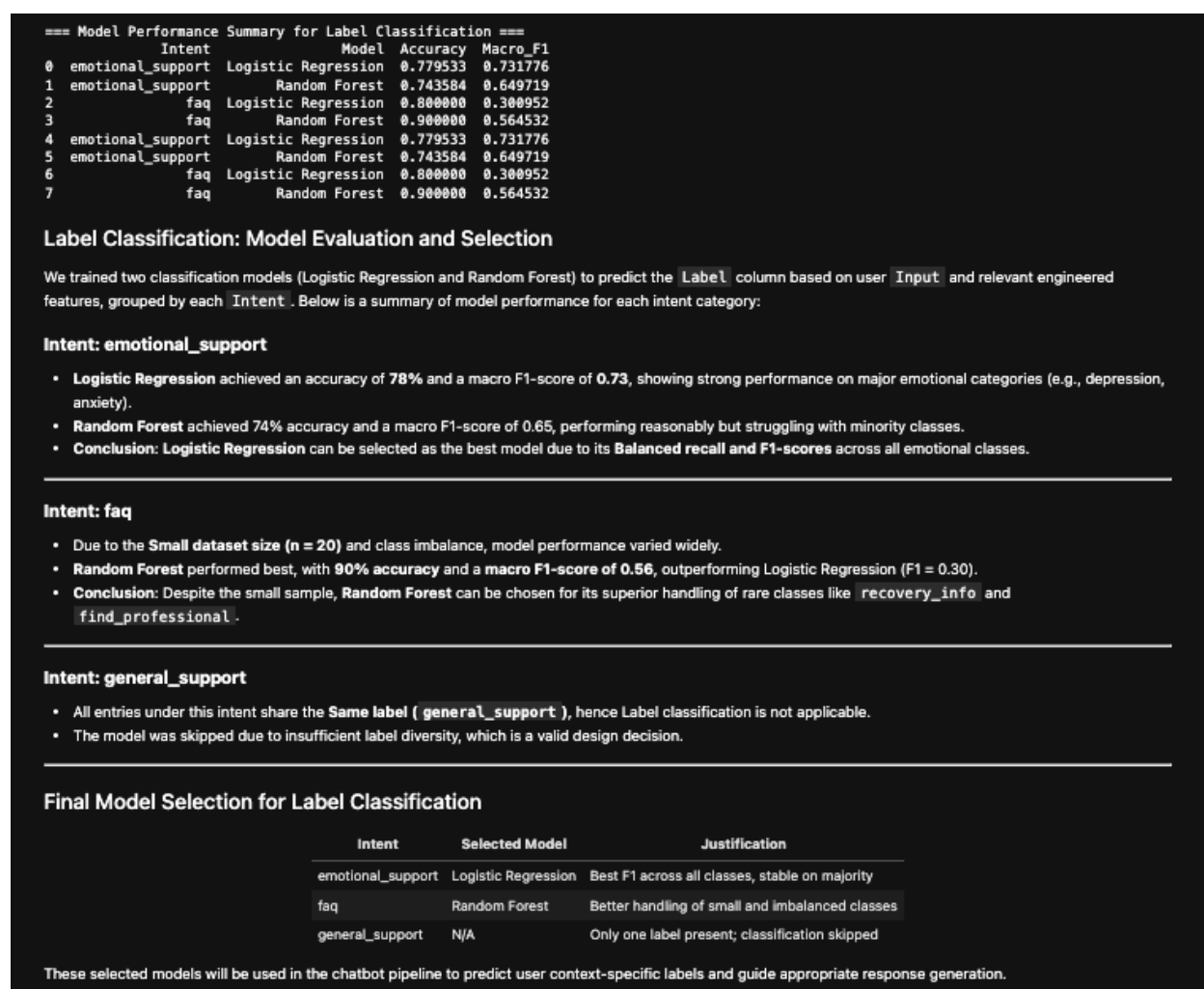


Fig 13. Label Classification Task

Based on the code results in Fig 13, Since label meanings varied across intents, we trained separate classifiers for `emotional_support` and `faq` messages using Logistic Regression and Random Forest. For `emotional_support`, Logistic Regression slightly outperformed Random Forest in terms of macro F1-score (~0.73 vs. ~0.65), demonstrating better recall for mid-frequency sentiment classes. However, for the `faq` intent, Random Forest handled the small and imbalanced dataset more effectively, producing a higher weighted F1-score and recall for rare labels. Given these findings, the best model per intent was selected based on performance within each subgroup, ensuring tailored, high-quality predictions for each type of user input.

Conclusion

In this milestone, we successfully progressed from feature engineering to training and evaluating classification models, forming the core of our AI-powered mental health chatbot system. We began by unifying three diverse datasets—counseling conversations, mental health FAQs, and sentiment-labeled statements—into a single, enriched dataset. Through task-specific feature engineering, we derived interpretable and semantically meaningful features such as `Statement_Word_Count`, `Has_Severe_Keyword`, and `Question_Word_Count`, which were validated through targeted exploratory analysis.

Feature selection followed a modular, intent-aware strategy, ensuring only relevant and non-redundant features were used per classification task. We trained and evaluated five models across two key classification tasks: Intent Detection and Label Classification. Random Forest was identified as the best-performing model for intent classification due to its robustness across imbalanced classes, while task-specific choices were made for label classification based on per-intent performance. All models were assessed using macro F1-scores, accuracy, and confusion matrices to ensure fair evaluation.

Overall, this milestone laid the technical foundation for the chatbot's intelligent understanding of user input. The insights and models developed here will directly support Milestone 3, which focuses on chatbot deployment, response generation, and user interaction.