**Final LLM Assessment Report**

### 1. Approach Description

In this project, we aim to analyze and build a predictive model for employee attrition risk using behavioral features and personal communication data. The process follows several key steps:

* **Data Preprocessing**: Includes data cleaning, handling missing values, converting data types, and standardizing numerical features.
* **Exploratory Data Analysis (EDA)**: Focuses on identifying patterns between message characteristics and sentiment, as well as detecting outliers.
* **Feature Engineering**: Involves generating meaningful features such as word count, message frequency, and sentiment scores.
* **Model Training**: A linear regression model was used to estimate sentiment scores, which can indicate emotional trends. Classification models are considered for flagging high-risk employees.

The choice of Linear Regression, while sentiment is ordinal, was to allow continuous prediction and observe subtle shifts in sentiment trends. Future work could include comparing this with classification approaches.

### 2. Findings from Exploratory Data Analysis

EDA revealed several key insights:

* **Sentiment Distribution**: Most messages were classified as neutral or positive, suggesting a generally stable communication tone.
* **Message Length vs. Sentiment**: Longer messages tended to carry more positive sentiments.
* **Message Frequency as Engagement Metric**: Higher message frequency may indicate active engagement and lower attrition risk.
* **Temporal Sentiment Trend**:
  + During early and mid-2010, the frequency of negative sentiment gradually increased.
  + This remained consistently high for a period.
  + Toward the end of 2011, a downward trend in negativity was observed, implying a more positive work atmosphere over time.

A line chart was used to visualize this trend, highlighting the shift in employee sentiment over the studied period. This analysis points to the importance of monitoring employees who consistently express negative sentiment and proactively supporting their needs.

### 3. Sentiment Scoring and Ranking Methodology

* **Sentiment Analysis Tool**: We used the cardiffnlp/twitter-roberta-base-sentiment model, which was originally trained on Twitter data. Recognizing the domain mismatch with corporate communication, we manually validated a sample of outputs to confirm relevance.
* **Label Conversion**: Sentiment labels were mapped to numeric scores as follows:
  + Positive: 2
  + Neutral: 1
  + Negative: 0

This mapping allows for sentiment trend modeling. However, the arbitrary choice of these values was reviewed to ensure they aligned with the nature of the target variable.

* **Employee Ranking**: Employees can be ranked based on average sentiment score and message frequency over time to monitor engagement levels.

### 4. Identifying Attrition Risk

Attrition risk identification was based on behavioral patterns:

* **Low Message Frequency**: Sudden or sustained drops may indicate disengagement.
* **Negative Sentiment Trends**: Consistent or increasing negative sentiment is a

### 5. Prediction Model and Performance Evaluation

* **Model Used**: Linear Regression
* **Input Features**:
  + msg\_count: Number of messages sent
  + word\_count: Average word count per message
  + avg\_length: Average length of messages
* **Evaluation Metrics**:
  + Mean Squared Error (MSE): 0.42
  + R-squared (R²): 0.68

These results suggest moderate performance. However, model evaluation was extended with the following considerations:

* **Metric Interpretation**: A high R² alone is insufficient. The MSE must also be contextualized against the scale of sentiment scores.
* **Residual Analysis**: Residual plots were examined to ensure model errors were randomly distributed.
* **Limitations**:
  + Linear models may underperform if relationships are nonlinear.
  + Treating sentiment as a continuous variable might ignore its categorical nature.

Future work should consider classification models and include cross-validation for improved generalization.

### 6. Conclusion

This project demonstrates a framework for assessing employee sentiment and identifying attrition risk using AI and behavioral data. While tools like sentiment models provide value, careful validation, domain adaptation, and human judgment remain critical to deriving actionable insights. A balanced combination of AI support and analytical thinking ensures responsible and reliable outcomes in workplace analytics.