**Literature Review**

**Models Used in Sentiment Analysis**

Sentiment analysis relies on various deep learning models, each with distinct strengths and limitations.

* **Traditional Models**:
  + **CNNs** are efficient at capturing local patterns (e.g., n-grams) and are computationally fast but lack the ability to model long-range dependencies.
  + **LSTMs** address this by capturing sequential relationships in text but are computationally expensive and struggle with large datasets.
  + **BiLSTMs**, an extension of LSTMs, improve contextual understanding by processing input in both forward and backward directions, albeit with even higher computational costs.
* **Embedding-Based Approaches**:
  + **Word2Vec** and **GloVe** provide static word embeddings based on semantic similarity. While effective in representing words, they fail to account for context, limiting their adaptability to nuanced text like mental health discourse.
* **Transformer-Based Models**:
  + **BERT** has revolutionized sentiment analysis with its bidirectional context understanding, enabling nuanced comprehension of text. However, its high computational requirements and interpretability issues make it challenging for clinical use.
  + **RoBERTa** enhances BERT's accuracy by optimizing training techniques but increases computational demands further.
  + **DistilBERT**, a lighter version, offers a balance between performance and efficiency, making it suitable for resource-constrained settings.

The progression from traditional models to transformers highlights significant advancements, yet challenges such as computational cost and interpretability remain.

**Applications in Mental Health**

Sentiment analysis has been increasingly applied to mental health monitoring due to the growing prevalence of social media platforms as outlets for emotional expression.

* **Early Detection**:  
  Sentiment analysis helps identify patterns indicative of conditions like depression and anxiety, facilitating timely interventions.
* **Aspect-Level Sentiment Analysis**:  
  This approach targets specific topics within text, such as identifying stress triggers like work or family issues. For example, “I love my job but feel overwhelmed” reveals positive sentiment toward the job and negative sentiment toward workload, enabling more granular insights.
* **Multimodal Analysis**:  
  By integrating text with visual data, such as images or videos, multimodal analysis provides a richer understanding of emotional states. Despite its potential, challenges like data processing complexity and computational demands remain significant barriers.

**Existing Gaps and Challenges**

* **Data Sparsity**:  
  The lack of annotated datasets specific to mental health sentiment limits model training and reduces generalizability across diverse contexts. This is especially problematic for identifying subtle expressions of mental health issues.
* **Scalability**:  
  Transformer models like BERT require substantial computational resources, making real-time and large-scale deployment difficult.
* **Interpretability**:  
  BERT and similar models are often criticized for their “black box” nature. This lack of transparency hinders clinical validation and trust among healthcare professionals. Solutions like RoBERTa and DistilBERT address some concerns by offering more efficient and interpretable architectures, but further improvements are needed.