# Investigating the Role of Sentiment in Motivational Strategies Using Transformer-Based Models: Associations With Psychiatric Traits

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## 1. Background

**Background:**

- Motivational deficits are common in psychiatric disorders (Fervaha et al., 2016),
- Sentiment in self-motivation strategies may be linked to anxiety, rumination, anhedonia, and self-esteem, however the emotional tone (sentiment) behind motivational strategies remains underexplored.
- Understanding associations between sentiment in motivational strategies and psychological trails may provide insights into cognitive and emotional patterns to improve interventions for individuals struggling with motivation.

**Objective:**

This study uses SiEBERT (Hugging Face, 2021), a BERT-based sentiment analysis model, to examine the sentiment expressed in self-reported motivational strategies and in association to psychological traits such as anxiety, rumination, pleasure, and self-esteem.

## 2. Methods

**Participants:** 312 participants were recruited online via Prolific, Inc. and prompted with the question: "What do you do to motivate yourself?" and provided free-text responses and self-reported scales.

- Temporal Experience of Pleasure Scale (TEPS) for anticipatory and consummatory anhedonia; State-Trait Inventory for Cognitive and Somatic Anxiety (STICSA) for anxiety; Ruminative Response Scale (RRS) for rumination; (Self Esteem Scale) for Self Esteem.

**Sentiment Analysis Model Selection:** SiEBERT and DistilBERT were compared to human-labeled sentiment scores using confusion matrices to evaluate accuracy, classification errors, and model agreement. SiEBERT was further analyzed for model accuracy.

**Statistical Analysis:**

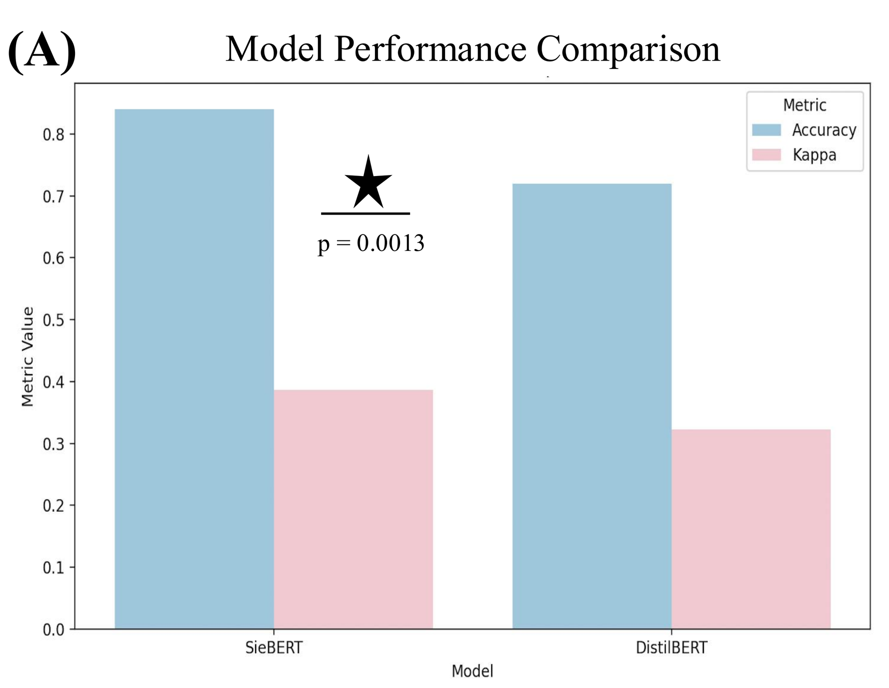
- After data cleaning, N=298 participant responses were analyzed in Python using SiEBERT to determine the underlying positive/negative sentiment behind motivational strategies.
- Descriptive statistics and 95% confidence intervals were calculated.
- Kruskal-Wallis tests examined sentiment differences across each behavioral level.
- Post-hoc Dunn test to identify specifically which groups differ after a Kruskal-Wallis test shows a significant result.

## 3a. Results: Model Performance

**(E)**

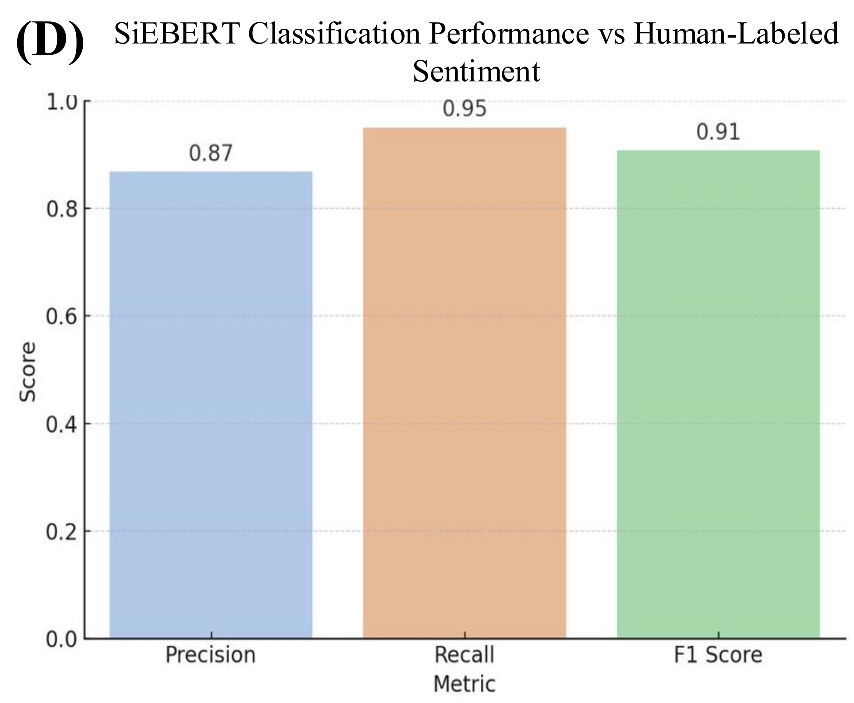
| Behavioral Variable | H-Statistic | Kruskal-Wallis p-value | Post-hoc Dunn Test | Mean | STD | Min | Max | 95% Confidence Interval |
|---|---|---|---|---|---|---|---|---|
| Anxiety | 66.32 | 0.02 | 0.026 | 35.00 | 12.79 | 21.0 | 84.0 | (33.55, 36.46) |
| Rumination | 71.70 | 0.05 | 0.007 | 43.49 | 15.32 | 22.0 | 86.0 | (41.75, 45.24) |
| Self Esteem | 16.65 | 0.78 | 0.047 | 15.94 | 4.18 | 4.0 | 28.0 | (15.46, 16.42) |
| Anticipatory Pleasure | 62.42 | 0.0075 | 0.004 | 42.64 | 7.82 | 14.0 | 60.0 | (41.75, 43.53) |
| Consummatory Pleasure | 49.37 | 0.0075 | 0.026 | 37.19 | 6.24 | 17.0 | 48.0 | (36.48, 37.91) |

**(A)**

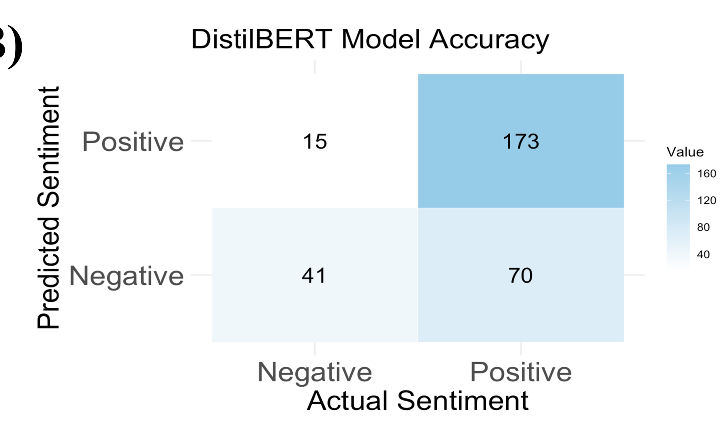



$$Accuracy\ Score = (TP + TN) / (TP + TN + FP + FN)$$

**(D)**




**(B)**




**(C)**

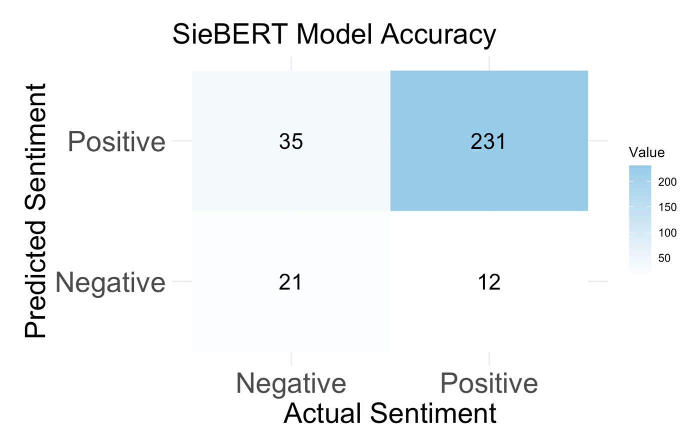



**Figure 1.** Model Performance and Psychological Measures
**(A)** SiEBERT achieved higher sentiment accuracy (**Accuracy: 0.84**) compared to DistilBERT (Accuracy: 0.72), demonstrated stronger agreement with human-labeled sentiment data (**SiEBERT Cohen's Kappa**: 0.3867; **DistilBERT Cohen's Kappa:** 0.3223), and made significantly fewer classification errors compared to DistilBERT (**McNemar's test: SiEBERT, p = 0.0013; DistilBERT p = 4.71x 10⁹**).
**(B-C)** Confusion Matrices for determining model accuracy using the models' predicted sentiment against the actual sentiment. *TP = true positive, TN = true negative, FP = false positive, FN = false negative.*
**(D) Precision (0.87):** When SieBERT predicts "positive," it's right 87% of the time; **Recall (0.95):** correctly identifies 95% of all true positive cases; **F1 Score (0.91):** strong overall balance.
**(E)** Statistical summary of behavioral variables. *STD = standard deviation*

## 3b. Results: Statistical Results and Discussion

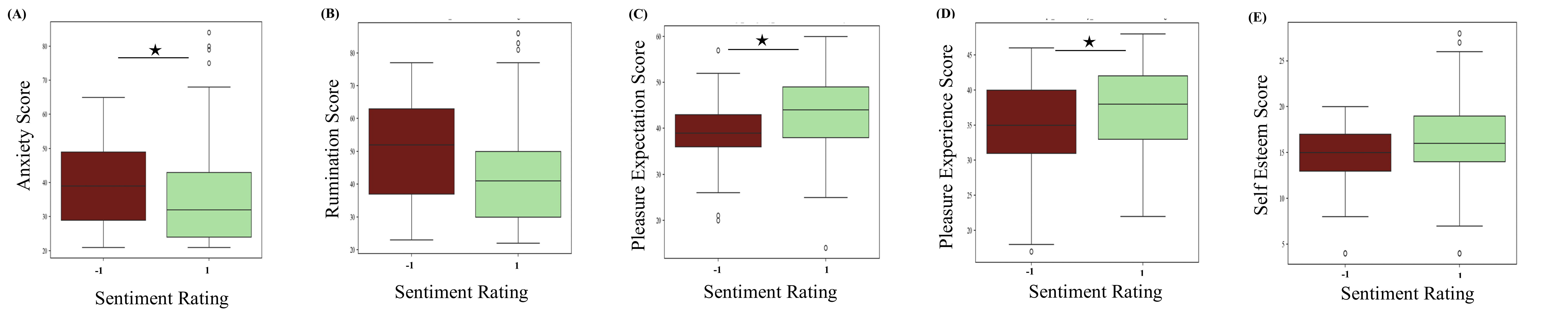



**Figure 4. Behavioral Scores Across Sentiment Ratings.**
**(A)** Anxiety scores show significantly higher values for individuals with negative sentiment (p = 0.02). **(B)** Rumination scores are higher in negative sentiment responses, with a broader range in this group. **(C)** Pleasure Expectation scores (TEPS A) are significantly higher in positive sentiment responses (p = 0.0075), suggesting individuals with more positive sentiment also report greater anticipation of pleasure. **(D)** Pleasure Experience (TEPS C) scores are also significantly higher in positive sentiment responses (p = 0.0075), but with substantial overlap. **(E)** Self-Esteem scores are notably higher in positive sentiment responses, indicating a potential relationship between positive self-evaluation and sentiment. Overall these results suggest that individuals with higher sentiment ratings tend to have higher pleasure anticipation and lower anxiety scores. *-1 = Negative sentiment, 1 = Positive sentiment*

## 4. Future Directions

- Incorporate neutral or mixed sentiment categories to capture a more nuanced emotional tone in motivational responses.
- Fine-tune transformer-based sentiment models on psychological datasets to improve model performance and test on larger datasets.
- Examine whether certain words or motivational approaches are more prevalent in positive vs. negative sentiment groups using TF-IDF.
- Analyze whether self-directed motivational statements (e.g., "I tell myself to keep going") differ in sentiment from other-directed strategies (e.g., "My family motivates me").

## 5. References & Acknowledgements

**References:**

1. Siebert. (2021). SiEBERT: sentiment-roberta-large-english [Machine learning model]. Hugging Face.
2. Fervaha, G., Foussias, G., Takeuchi, H., Agid, O., & Remington, G. (2016). Motivational deficits in major depressive disorder: Cross-sectional and longitudinal relationships with functional impairment and subjective well-being. Comprehensive Psychiatry, 66, 31–38. https://doi.org/10.1016/j.comppsych.2015.12.004

**Acknowledgements:**

This work was funded by NIMH K01 MH 120433 for LSM.