This research investigated the use of natural language processing (NLP) to track negative emotions in adolescents' daily lives by analyzing their text responses. The study compared idiographic models, which are personalized to individuals, against nomothetic models, which are group-based, in predicting emotional fluctuations. Different NLP techniques, including dictionary-based approaches, topic modeling, and GPT-derived emotion ratings, were evaluated for their effectiveness. The findings suggest that while nomothetic models offer broad applicability, idiographic models can provide greater precision in tracking individual emotional changes, particularly when combining various NLP methods and selecting the best model for each person. Ultimately, this work highlights the potential of personalized text analysis for enhancing emotion monitoring and informing tailored mental health interventions for young people.

Question 1: What were the main findings of the study regarding the comparison between idiographic and nomothetic models for predicting negative affect in adolescents?

Response: The study's main findings highlight that while nomothetic (group-level) models showed good overall performance in predicting negative emotions at a group level, their ability to accurately track within-person fluctuations varied considerably across individuals. When evaluated per participant, the mean performance of nomothetic models decreased significantly. In contrast, idiographic (individual-level) models demonstrated comparable average performance to nomothetic models in terms of R^2 but yielded lower prediction error (RMSE), indicating improved within-person precision. Importantly, when the best-performing model (which was often idiographic) was selected for each participant, significant correlations between predicted and observed emotion scores were found for a large majority (90.7–94.8%) of them. This suggests that personalized models may offer greater predictive precision with sufficient within-person data.

Question 2: How did different Natural Language Processing (NLP) techniques compare in their ability to predict negative emotions within individuals?

Response: The study compared three main NLP approaches: dictionary-based (LIWC+VADER), topic modeling (LDA), and GPT-derived ratings. The findings indicate that GPT generally showed better performance for predicting negative affect, sadness, anger, and nervousness when these approaches were used individually in idiographic models, achieving R^2 values around 0.10 for negative affect and sadness. However, while GPT had relatively strong R^2 values, it also had a higher RMSE compared to combined models, suggesting a higher average prediction error. LIWC+VADER and LDA generally demonstrated poorer predictive performance with the lowest average R^2 values and fewer significant associations. Overall, the contextual understanding provided by GPT appeared more effective in capturing within-person emotional fluctuations compared to the other individual methods. However, combining all NLP approaches often led to the most robust and reliable emotion predictions by balancing the capture of variability and minimizing prediction errors.

Question 3: Did the study find evidence of individual differences in how adolescents express negative emotions through language?

Response: Yes, the study found substantial between-person differences in both model performance and the linguistic features that predicted negative affect. Even among the highest-performing models, the specific text features that contributed to predicting negative emotions varied across individuals. For example, one participant exhibited more negative emotions when using family-related words, while another showed greater negativity when focusing on the past or work-related topics. This highlights that language is inherently idiosyncratic, with individuals expressing emotions in unique and context-

dependent ways. The variability in feature importance across participants supports the idea of creating person-specific profiles to understand the specific contexts in which negative emotions arise.

Question 4: What are some of the limitations of using NLP to track emotional fluctuations, as identified by the study?

Response: The study identified several limitations:

- The need for large amounts of within-person data to capture the nuanced dynamics of emotional expression. Subtle emotional changes may only become apparent with extensive exposure to an individual's language use.
- The overall predictive accuracy was modest, leaving significant room for improvement.
- The text data in this study consisted of responses to specific questions, which may limit the generalizability of the findings to other types of text, such as social media posts or text messages.
- GPT models lack transparency in how inferences are generated and have difficulties in reproducing results due to their probabilistic nature.
- Dictionary-based approaches (like LIWC) can neglect context, leading to potential misinterpretations.

Question 5: What future research directions are suggested by the study to enhance the tracking of emotional fluctuations using NLP?

Response: The study suggests several avenues for future research:

- Collecting larger within-person datasets, potentially from daily-life communications.
- Incorporating additional modalities (e.g., vocal features, facial expressions, passive sensors from smartphones or wearables) alongside text to enhance predictive accuracy.
- Exploring whether individuals differ not only in the text features but also in the types of modalities that best capture their emotional states.
- Developing hybrid approaches that integrate both individual-specific and group-level information.
- Incorporating text from diverse sources such as social media and conversational exchanges.
- Optimizing the balance between nomothetic and idiographic approaches, potentially through fine-tuning techniques for LLMs like GPT.
- Developing methods that combine the powerful inference capabilities of GPT with more transparent analytical approaches.