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Sentiment Analysis of Slang Language Trends in Generation Alpha on Social Media Using BERT

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Abstract – *Generation Alpha is a group growing up in an era of rapid digital technology advancement. Unlike previous generations who experienced a transition into technology, Generation Alpha demonstrates unique communication characteristics, particularly in their frequent use of slang, which is often difficult for older generations to understand. This gap in language understanding can lead to miscommunication, especially when the meaning of slang is misinterpreted. This phenomenon presents a challenge in establishing intergenerational communication, especially in digital and social media contexts where informal language is dominant. This study aims to explore the effectiveness of AI models in analyzing the sentiment of slang language used by Generation Alpha. Three BERT-based models were utilized in this research: BERT, RoBERTa, and DistilBERT. These models were selected based on their performance and efficiency in natural language processing (NLP) tasks, particularly in text classification and sentiment analysis. The dataset consists of 24,958 slang-based posts collected from users on the social media platform X. The analysis shows that DistilBERT achieved the highest accuracy score of 0.83, followed by BERT (0.82) and RoBERTa (0.81). These findings suggest that BERT-based models, especially DistilBERT, perform reliably in identifying the sentiment behind slang expressions used by Generation Alpha and hold potential for implementation in AI-based moderation or social media monitoring systems.*

Keywords: *BERT; Gen Alpha; Sentiment; Slang Language*

I. INTRODUCTION

Generational differences influence how individuals communicate with the world around them. These differences are shaped by social environments, cultural contexts, and most importantly, access to technology. People who born before the digital era experienced minimal exposure to digital tools, whereas those born during and after the rise of the internet and smartphones live in a world where technology is deeply embedded in everyday life. According to McCrindle (McCrindle et al., 2009), generations can be categorized by their birth years: the Builders (before 1946), Baby Boomers (1946–1964), Generation X (1965–1979), Generation Y or Millennials (1980–1994), Generation Z (1995–2009), Generation Alpha (2010–2024), and Generation Beta (2025–2039). Of these existing generation in 2025, Generation Alpha is the most digitally native, having been born during a time of advanced digital connectivity (McCrindle & Fell, 2021).

Generational characteristics can be observed through language use, especially slang language. Slang is an informal form of language that reflects cultural trends and identity. For example, Generation Y usually uses the term “best friend” to describe a “good friend”. Generation Z uses the term “bestie” and generation Alpha uses the term “pookie” (Rachmijati & Cahyati, 2024). Generation Alpha often creates words from digital media and platforms such as TikTok, Discord, and YouTube Shorts (Subhan et al., 2025). Unlike Generation Z, who can adapt slang for both informal and formal settings, Generation Alpha often lacks the ability to distinguish between casual and standard language in communication(Paoleti et al., 2025).

The frequent and evolving use of slang creates a challenge for tasks like sentiment analysis, which aims to determine the emotional tone behind textual content. Sentiment analysis is a subfield of natural language processing (NLP) that seeks to identify opinions, feelings, or attitudes from textual data (Damar et al., 2024). However, newly emerging slang expressions are often not included in sentiment lexicons or dictionaries, thereby reducing model accuracy (Thelwall & Cambria, 2021). Because of this, understanding the sentiment of Generation Alpha's slang is not only linguistically interesting but also relevant for practical applications such as online safety monitoring, brand feedback analysis, and education.

This study focuses on two main contributions: conducting sentiment analysis on the slang language used by Generation Alpha to better understand their daily communication patterns and evaluating the performance of three BERT, RoBERTa, and DistilBERT in analyzing this form of language. Transformer-based models have revolutionized sentiment analysis tasks by providing deep contextual understanding. BERT (Bidirectional Encoder Representations from Transformers), developed by Devlin et al. (Devlin et al., 2018), processes text bidirectionally and generates contextual embeddings that significantly improve performance in NLP tasks. RoBERTa (Liu et al., 2019) is an optimized version of BERT that removes the Next Sentence Prediction (NSP) objective and is trained with larger batch sizes and datasets, resulting in improved accuracy. Meanwhile, DistilBERT (Sanh et al., 2019) is a smaller, faster, and more efficient variant of BERT that retains 97% of BERT’s performance while being more suitable for resource-constrained environments.

Christodoulou (Christodoulou, 2023) conducted a study on depression classification from English social media text using RoBERTa and DeBERTa, finding that RoBERTa has the best classification performance. Akintoye (Akintoye et al., 2024) reported that RoBERTa outperformed DeBERTa and DistilBERT in detecting suicidal ideation from Twitter. Similarly, Dryankova (Dryankova et al., 2024) demonstrated that RoBERTa was superior to DistilBERT in identifying check-worthy claims in multilingual Twitter datasets. However, Nirmala (Gandhi et al., 2025)concluded that although DistilBERT has slightly lower accuracy compared to RoBERTa, it offers significant advantages in speed and memory usage, making it ideal for multilingual settings, chatbot systems, and mobile applications.

In line with these findings, this study evaluates BERT, RoBERTa, and DistilBERT on sentiment classification of Generation Alpha's slang language. This not only helps determine which model performs best but also contributes to the broader understanding of how machine learning can process dynamic and evolving forms of human language.

II. METHODS

The research process involved data collection, text preprocessing, labeling, fine-tuning, and evaluation. The data was collected by scraping posts published by users on X (formerly Twitter) from January 2022 to August 2024 (Priccilia, 2025). A total of 29,550 user posts were obtained. The collected posts contain slang keywords commonly used by Generation Alpha, such as the following.

- Fresh and Creative:
  Aura, Baddie, Cheugy, Drip, Fanum Tax, Looks Maxxing, Mewing, Mog, Periodt, Rizard of Oz, Sheesh, Sigma, Skibidi, Yeet
- Flippant Slang:
  Big L, Big W, Glow Up, Low Vibrational, Lowkey, Mad Lit, Negative Aura, Red Flag, Green Flag, Vibe Check
- Imitative Slang:
  Basic, Bet, Beta, Cap, Clout, Cringe, Extra, Fax, Fire, Flex, Ghost, Gucci, Lit, Lore, Mood, Salty, Shook, Slay, Sus, Tea, Thirsty, Tweaking, Woke
- Acronym:
  GOAT
- Clipping:
  Ate, Bop, Bussin, Delulu, Gyatt, Ick, Mid, Peep, Pookie, Ratio’d, Rizz, Rizzler, Snack, Snatched, Squad, Stan, Sus, Vibe, Vibin, Yapping

After collecting, the text data underwent preprocessing. The optimal preprocessing sequence, as suggested by Palomino (Palomino & Aider, 2022), includes: removing metadata, lowercasing, removing punctuation, URLs, and excess whitespace, translating emoticons and emojis, expanding acronyms and slang, handling negations, removing stop words, tokenization, and removing short words. Adopting this approach, the preprocessing in this study is divided into several steps as illustrated in Figure 1.

The cleaned text is labeled using the TextBlob, VADER, and Flair libraries. TextBlob, VADER, and Flair achieved accuracies of 0.55, 0.56, and 0.49, respectively, for sentiment labeling on the Sentiment140 dataset (Sârbu et al., 2024). TextBlob is an NLP library that provides an API for tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, and more (Loria, 2025). In TextBlob, if the polarity is below 0, the sentiment is negative; if it is 0, the sentiment is neutral; and if it is above 0, the sentiment is positive. VADER is a rule-based model trained for sentiment analysis tasks (Hutto & Gilbert, 2014). In VADER, if the compound score is above 0.05, the sentiment is positive; if it is below -0.05, the sentiment is negative; and if it is between -0.05 and 0.05, the sentiment is neutral. Flair is an NLP framework used for sequence labeling, text classification, and language modeling for training and distribution purposes (Akbik et al., 2019). In Flair, the sentiment labels are POSITIVE and NEGATIVE. In this study, the sentiment labels from TextBlob, VADER, and Flair will be voted to determine the final label.

After labeling, sentiment analysis is performed using three sentiment labels: positive, neutral, and negative with the BERT (Devlin et al., 2018), DistilBERT (Sanh et al., 2019), and RoBERTa (Liu et al., 2019) models. BERT is used because it is the state-of-the-art model for sentiment analysis. DistilBERT and RoBERTa are variations of BERT. DistilBERT is a smaller version of BERT consisting of 6 layers, while RoBERTa is a version of BERT trained on a larger dataset and for a longer period. The differences between BERT, DistilBERT, and RoBERTa are shown in Table 1.

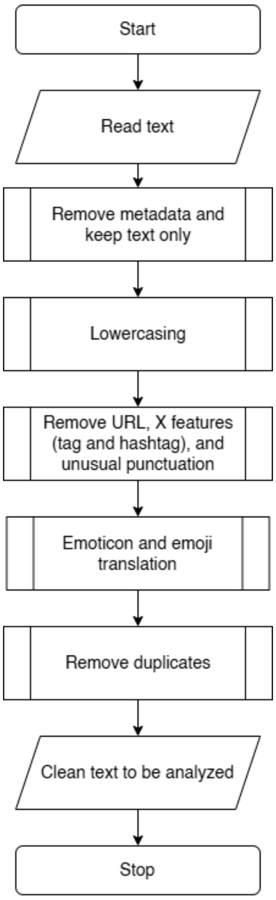


Figure 1. Dataset Processing Steps

Table 1. Comparison of BERT Model Variations

Model	Parameter	Layer
BERT (Devlin et al., 2018)	110M	12
RoBERTa (Liu et al., 2019)	125M	12
DistilBERT (Sanh et al., 2019)	66M	6

To evaluate the performance of the model, the metrics accuracy, F-measure, precision, and recall are used. These metrics are the most used to visualize and assess the performance of classification algorithms (Xu et al., 2022).

III. RESULTS AND DISCUSSION

Based on the data collection process, a clean dataset was obtained, with statistics presented in Table 2. Labeling was conducted through a voting mechanism combining the sentiment results from TextBlob, VADER, and Flair. According to the analysis, the top five slang terms associated with negative sentiment are Low Vibrational, Negative Aura, Shook, Basic, and Yapping. The top five slang terms for neutral sentiment are Mewing, Fanum Tax, Gyatt, Tweaking, and Periodt. Meanwhile, the top five slang terms for positive sentiment are Extra, Vibe, Squad, Sheesh, and Lore.

Table 2. Dataset Distribution

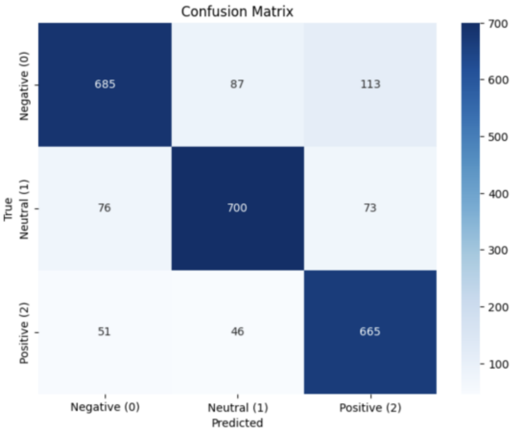
Label	Textblob	Flair	VADER	Final label
Negative	5,526	14,602	7,228	7,624
Neutral	10,442	0	8,469	8,843
Positive	8,990	10,356	9,261	8,491
Total	24958			

Each model underwent fine-tuning. The model with the best evaluation result was saved. The test results for BERT, RoBERTa, and DistilBER were 0.82, 0.81, and 0.83, respectively. Detailed results are presented in Table 3. Among the baseline sentiment tools, VADER performed best with an accuracy of 0.84, while TextBlob achieved 0.74. Flair could not be directly evaluated for neutral sentiment classification, as it does not support neutral labels.

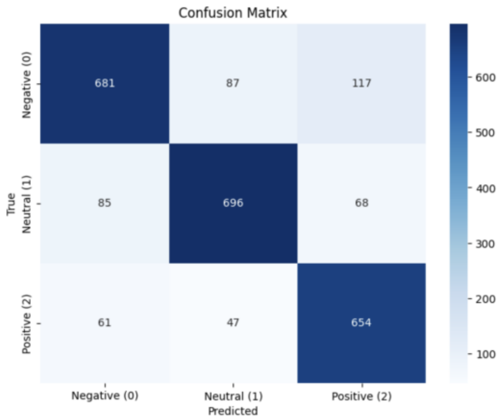
Table 3. The Results of BERT Model Variations

Metric	BERT	RoBERTa	DistilBERT
Precision	0.820	0.813	0.830
Recall	0.820	0.817	0.827
F1-Score	0.820	0.817	0.827
Accuracy	0.820	0.810	0.830
Loss	0.516	0.518	0.517

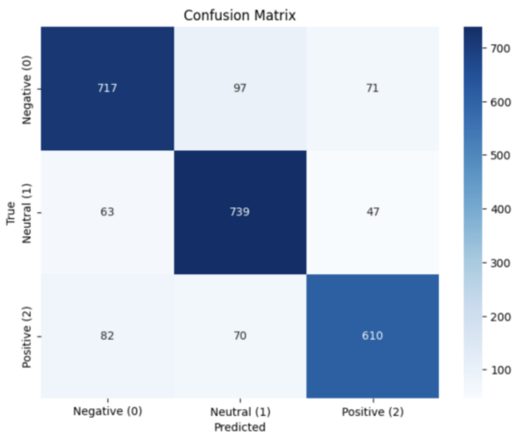
These findings indicate that all three BERT-based models are capable of learning the sentiment patterns associated with slang used by Generation Alpha. Surprisingly, DistilBERT, a compressed and lightweight version of BERT, slightly outperformed both BERT and RoBERTa in this task. Figure 2 presents the confusion matrices for the three transformer-based models: BERT, RoBERTa, and DistilBERT.



(a)



(b)



(c)

Figure 2. Confusion Matrix of (a) BERT, (b) RoBERTa, and (c) DistilBERT Models for Predicting Sentiment of Generation Alpha Slang Language.

This outcome suggests that DistilBERT, which is less data-hungry and has fewer parameters, is well-suited for medium-sized datasets such as the one used in this study (~25,000 samples). Its efficiency and faster training time make it a strong candidate for sentiment analysis tasks involving slang language and others dynamic language. However, larger models such as BERT and RoBERTa may be more profitable from larger-scale data. Their relatively lower performance in this study may be happen due to underfitting, as they require more data to leverage their full potential. RoBERTa, as the most complex model, has the lowest performance likely because of its higher complexity which may not be optimal for medium-scale datasets. Therefore, future work should focus on adding more dataset with additional labeled samples by incorporating human annotations for improved reliability of label. Furthermore, updating slang lexicons periodically and exploring model performance across multilingual could beneficial to enhance generalizability of model.

IV. CONCLUSION

This study demonstrates that the slang used by Generation Alpha exhibits diverse and unique sentiment characteristics that are not yet represented in traditional dictionaries. Most of the adopted slang terms fall into the categories of Fresh and Creative, Flippant Slang, Imitative Slang, and Clipping. The most frequently used slang terms are “low vibrational” to express negative sentiment, “mewing” for neutral sentiment, and “extra” for positive sentiment.

By fine-tuning BERT and its variants, the results show that DistilBERT achieved the highest accuracy in predicting the sentiment of Gen Alpha slang (0.83), followed by BERT (0.82) and RoBERTa (0.81). These findings indicate that transformer-based models are effective in handling sentiment analysis of Generation Alpha’s slang language.

This study concludes that the development of adaptive linguistic models is essential to accommodate evolving language usage across generations, particularly in the context of social media and digital communication. For future work, the data can be labeled manually or with human intervention to improve the reliability and accuracy of the sentiment labels.

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