

Comparison of Sentiment Analysis in Internship Feedback from Hospitality, Educational Institutions, and Other Industries: An Analysis Using TextBlob and VADER

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Abstract

This quantitative research examines how VADER and TextBlob sentiment analysis tools process feedback data from the host organizations of 124 Thai university interns. The research uses supervisor evaluations from hospitality, education institutions, and other industries to determine how each tool identifies positive, negative, and neutral sentiments. The Mann-Whitney U test was applied to compare the sentiment scores produced from preprocessed internship comments by two analysis tools. The research showed that education sector feedback received similar assessments from both tools despite the apparent difference in polarity spread, while hospitality and other sectors produced distinct results despite showing similarity in the polarity terms. The research indicates that sentiment interpretation depends on the analysis tool, suggesting the need to understand the fundamental discrepancy between these tools in labelling negativity and positivity for feedback on internships.

Keywords: sentiment analysis, internship feedback, Thai university students

1. Introduction

Thailand's job market is undergoing a transformation, driven by technological advances, shifting demographics, and changing industry demands. From a macro perspective, the nation's labor pool is projected to shrink from around 38 million workers today to roughly 22.8 million in fifty years, largely because of persistently low birth rates and a rapidly aging population (Yonpiam, 2025). Traditional manufacturing sectors are struggling to adapt to shifting market conditions, such as a surge in low-cost imports from China in the automotive industry and the existing automotive giant's reduction and relocation of their business in Thailand (Post Reporters, 2024), while technology sector is ready for expansion, as can be seen in Google's announcement of a 1 billion dollar investment in a Thai data center and cloud region that is expected to create 14,000 jobs until 2029 (Reuters, 2024). Tourism industry is also projected to open up employment, especially for multilingual workers (Singkala and Monpanthong, 2025).

In the light of these shifts, contemporary internship programs have become indispensable for getting Thai university students ready for a job market that is constantly evolving. Internships serve for connecting real-world practice internships with hands-on skills across sectors such, as tourism, education, business, media and technology. Against this backdrop, this study examines the process of analyzing the sentiments expressed by host organizations on Thai university students' internship experiences, as such analysis can help identify strength and potential issues in intern performance and will be a valuable resource for improving the future internship program. To achieve this, sentiment analysis tools such as VADER and TextBlob were employed for examining feedback in different fields and analyzing how these tools could be useful for precise assessment of current practices surrounding internships. In order to verify the accuracy of sentiment analysis by these tools, the sentiments expressed in supervisor feedback in three sectors, i.e., hospitality, education, and other industries, were classified into positive, negative, and neutral categories by each tool. Then the results were compared for the purpose of examining differences in how these two tools interpret sentiments. In the end, the study aims to determine whether the choice of sentiment analysis tool influences the overall interpretation of internship feedback, as well as to reveal discrepancies between VADER and TextBlob in identifying positive and negative sentiments in short evaluative texts.

Based on the said objective, the study hypothesized that internship evaluation comments contain positive, negative, and neutral sentiments across the three industry sectors, and that the sentiment scores from the two analysis tools would show a certain level of discrepancies, reflecting how differently each tool interprets the internship feedback. Finally, the study proposes that the choice of sentiment analysis tool influences the overall interpretation of internship feedback, particularly in identifying positive and negative sentiments in short evaluative comments.

2. Previous Studies

2.1 Internship in modern days

Internships in Thailand play a crucial role that bridges work-integrated learning programs which connects academic education to professional employment. Students who participate in internships gain industry knowledge and practical experience, as well as builds professional connections at their workplace (Giousmpasoglou & Marinakou, 2021). Empirical studies demonstrated that properly managed internships help students develop professional abilities and boost their job readiness and career prospects (Gutiérrez-Pulido & Orozco-Rodríguez, 2025; Yeong et al., 2024; O'Connor & Bodicoat, 2016). Aligning with this international trend, multiple studies on student internships have been implemented in Thailand, especially using experiential learning theory to analyze student learning through Kolb's experiential learning cycle (Kolb, 1984) which involves concrete experience followed by reflection, conceptualization, and active experimentation (U-senyang, 2024; Kingkaew et al., 2019; Tirasriwat et al., 2024).

In modern days, employers demand digital competence and soft skills from their workforce so that internships focus on teaching these essential skills (Linajari, 2024; Santiago & Gil, 2025; Losekoot et al., 2018; Patacsil & Tablatin, 2017). Research conducted in Thailand during recent years exhibits that students who demonstrate strong literacy skills and logical thinking abilities achieve better results in their internships (Imjai et al., 2024; Pantaruk et al., 2025), indicating that these competencies directly affect student employability and determine the success of internships.

However, multiple operational obstacles continue to affect the internships in Thailand. For instance, the current internship system fails to connect practical experience to

employment readiness due to a lack of effective career preparation methods (Yi et al., 2025) and the work environment during internships remains substandard because students face excessive work responsibilities and insufficient staff numbers and insufficient resources (Vithawat et al., 2024).

Research about internship feedback from host organizers remains scarce despite the expanding number of studies about this topic. Nevertheless, the evaluation of supervisor feedback about internships holds essential value, since it demonstrates both the success of internship programs and the degree to which students achieve their learning objectives.

2.2 Sentiment Analysis

The field of natural language processing (NLP) includes sentiment analysis as its fundamental component which focuses on automated extraction of subjective information from textual content (Mao & Zhang, 2024). This field has enhanced more important because user-generated content on platforms including product reviews and social media comments continues to grow exponentially (Chaturvedi et al., 2018). The main goal of sentiment analysis involves text sentiment detection which results in positive, negative or neutral classifications, while researchers also work to identify additional emotional states (Bose et al., 2020). Although a majority of sentiment analysis tools analyze English content, researchers can also analyze sentiments in Chinese and Thai languages (Wu & Zhuo, 2015; Nishiwaki et al., 2023).

The three main approaches for sentiment analysis include lexicon-based method, machine learning-based method, and deep-learning and hybrid approaches (Rani et al, 2021). The lexicon-based method uses pre-defined word lists which contain sentiment values to evaluate text sentiment (Taboada et al, 2011). An example of a lexicon-based sentiment analysis tool is VADER (Valence Aware Dictionary and sEntiment Reasoner) (Hutto & Gilbert, 2014), which produces assessment scores based on polarity, especially for short text in social media. TextBlob (Loria, 2018), the Python library for lexicon-based analysis, also enables users to obtain polarity as well as subjectivity scores. In contrast, machine learning- based approaches involve training algorithms on labeled datasets to recognize patterns and classify sentiments (Agarwal & Mittal, 2015). A prominent example of this approach is the use of BERT-based models, such as FinBERT and RoBERTa, which are transformer architectures fine-tuned for sentiment classification tasks (Araci, 2019; Deng & Liu, 2025). The deep learning methods

for sentiment analysis use RNNs, LSTMs, CNNs, and Transformers to automatically discover text features which include semantic and contextual elements. These models achieve superior results than conventional methods due to their ability to detect intricate linguistic patterns and contextual information which leads to better sentiment classification accuracy. While deep learning methods are most effective for modern sentiment analysis, they require large-labeled datasets and lack interpretability (Tang et al., 2015).

Despite the advancements in sentiment analysis techniques, several challenges persist. For instance, the definition of sentiment remains inconsistent and researchers face challenges when measuring it, while existing models demonstrate bias and fairness issues and show limited ability to adapt between different domains (Venkit et al., 2023). Besides, the analysis of human language complexities remains a challenge, as researchers struggle to detect sarcasm, irony, and metaphor in text data (Aftab, 2023).

The field of sentiment analysis has multiple extensive applications which span different fields of study. In the businesses sector, sentiment analysis is used to track customer opinions which helps them monitor brand reputation and develop marketing plans (Aguilar-Moreno et al., 2024). In politics, the analysis of public sentiment through sentiment analysis helps political organizations understand how citizens react to policies and political candidates (Ansari et al., 2020). The healthcare industry leverages sentiment analysis to analyze patient feedback which enables them to enhance their service delivery (Denecke & Reichenpfader, 2023). Moreover, the analysis of social media content helps organizations track public emotions during both political events and emergency situations (Ma'aly et al., 2024; Win Myint et al., 2024).

In conclusion, the analysis of public sentiment through sentiment analysis serves for understanding public opinion and sentiment in today's digital age (Ligthart et al., 2021; Holderness et al., 2019). While significant progress has been made in developing techniques to analyze sentiment, ongoing research is essential to address the existing challenges and enhance the accuracy and applicability of sentiment analysis across various domains.

3. Methodology

The research participants consisted of 124 students from the Department of Business English at a private Thai university who completed the mandatory internship course in 2023

and 2024. This sample size represents the total number of interns from these cohorts, which comprise the most recent available internship data. The students worked in different sectors, particularly in hospitality and tourism ($n=67$), e.g. hotels, restaurants, and travel agencies; education ($n=21$), e.g. elementary schools and high schools; and other industries including manufacturing and trading ($n=36$), e.g., automotive companies and agricultural product traders, for approximately 540 hours throughout their internship period. The students needed to maintain daily logs in their assigned logbooks which required them to document their work hours, duties, and their professional insights. The supervisors from the students' workplaces assessed their performance, attitude, and progress through written evaluations which they submitted in English or Thai after the internship ended.

The researchers collected supervisor evaluations for analysis purposes, and translated Thai comments into English through two Thai English instructors who verified and improved the accuracy of the translations. Then the research team comprising the four English language experts performed error correction on all English comments which showed obvious grammatical and spelling mistakes. The participant confidentiality were protected through name replacement with pronouns such as "I," "he," and "she" and omitted workplace identities.

The study employed VADER and TextBlob as sentiment analysis tools to process textual data efficiently and reliably. These tools were chosen as sentiment tools for this study, on the ground that they offer simple operations and clear results for processing brief informal texts from social media platforms. Both are lexicon-based tools widely recognized for their simplicity, interpretability, and effectiveness in analyzing short, informal, or social media-style texts. As the supervisor feedback primarily consisted of brief comments similar in nature to social media posts, these tools were deemed more appropriate than machine learning-based models that require complex processing. Another reason for choosing these tools is that the quality of VADER and TextBlob has been demonstrated in several prior studies using them (In & Chanchamnan, 2026; Huda et al., 2025; Dahal et al., 2025).

The validity of the research instruments was ensured through the use of real internship feedback from three industries, established sentiment analysis tools (VADER and TextBlob), and standardized scoring frameworks based on polarity evaluation. Also, the data were carefully examined by the multiple English language experts, i.e., the co-authors of this study. Meanwhile, reliability was ensured through the repeated validation of the data analysis

using the two tools for reproducing the consistent outputs and verification of the datasets by the co-authors of this study.

TextBlob and VADER use separate methods to generate sentiment scores. TextBlob generates two essential scores which include polarity and subjectivity. The polarity score extends from -1.0 to +1.0 where negative values indicate negative sentiment and positive values indicate positive sentiment, and values near zero indicate neutral sentiment. The subjectivity score extends from 0.0 to 1.0 to show the level of personal opinion or factual content in a text (Suanpang & Kaewyong, 2021). Meanwhile, VADER produces four sentiment scores which include positive, negative, neutral, and compound. The first three sentiment categories show the percentage of text content that belongs to each category, while the compound score between -1.0 and +1.0 represents a weighted average of all lexicon ratings in the text (Youvan, D. C. 2024). A compound score above 0.05 typically indicates positive sentiment, below -0.05 indicates negative sentiment, and between these thresholds indicates neutral sentiment. VADER incorporates not only word-level sentiment values but also punctuation, capitalization, degree modifiers, and negations, making it particularly effective for analyzing short messages.

The sentiment analysis with TextBlob and VADER evaluated internship feedback from hospitality, educational institutions, and other industries by assigning positive, negative or neutral labels, based on their calculated scores. The researchers built TextBlob and VADER on Google Colab which operates as a free cloud-based platform that enables users to execute Python code through their web browser.

The Mann-Whitney U test was applied to evaluate mean and median values for each sector. The Mann-Whitney U test, which is the non-parametric statistical method, enables researchers to evaluate independent groups for their continuous or ordinal data points. The method operates without requiring normal data distribution, making it suitable for small or skewed samples and evaluating differences by ranking observations. The test produces three main results, which include the U statistic, a p-value for significance, and sometimes effect size measures like rank-biserial correlation (Nachar, 2008). In that sense, the Mann-Whitney U test proves suitable for TextBlob and VADER result comparison, since the study analyzes independent non-normal sentiment scores that show skewed distributions. The process of

sentiment analysis for internship feedback using TextBlob and VADER follows the sequence as shown in Figure 1.

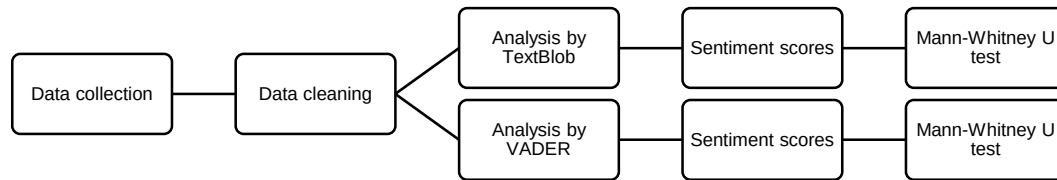


Figure. 1 Process of sentiment analysis of Internship feedback using TextBlob and VADER (created by the author)

4. Findings

The following section presents the results from TextBlob and VADER sentiment analysis. The two bar graphs in Figures 1 and 2 show the sentiment scores (positive, neutral, and negative) produced by TextBlob and VADER for the hospitality industry dataset. The TextBlob analysis resulted in 58 positive, 4 neutral, and 5 negative classifications, while VADER produced 57 positive, 1 neutral, and 9 negative classifications. The two tools produced matching results which demonstrated that positive sentiments occurred much more frequently than neutral and negative sentiments.

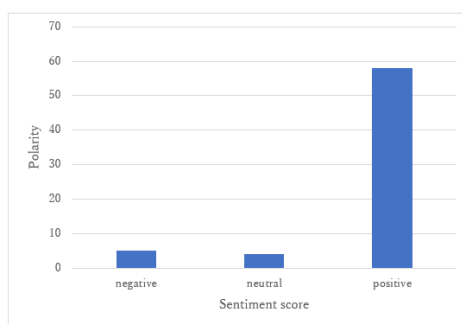


Figure 2. Internship scores in hospitality industry (analyzed by TextBlob)

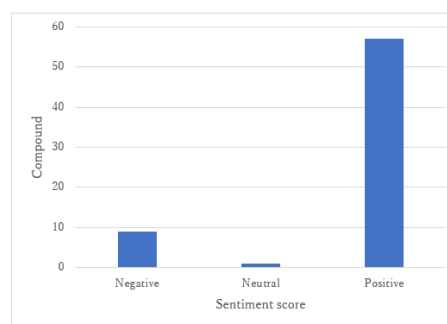


Figure 3. Internship scores in hospitality industry (analyzed by VADER)

The boxplot in Figure 4 shows that most comments have positive sentiment which ranges from 0.2 to 0.5 on the interquartile range, while the median value is at 0.4. Although a few outliers fall below zero, suggesting the presence of negative opinions, the overall distribution skews toward positivity. The boxplot in Figure 5 demonstrates a median value of

0.9, which indicates that most comments contain strong positive content. The interquartile range of this distribution extends from 0.7 to 1.0, which indicates that sentiment levels show consistent patterns. Nonetheless, several extreme outliers below zero, extending to around -1.0, reveal a small number of highly negative cases. The first dataset contains comments with moderate positive sentiment at different levels, while the second dataset shows dominant strong positive comments with occasional extreme negative opinions.

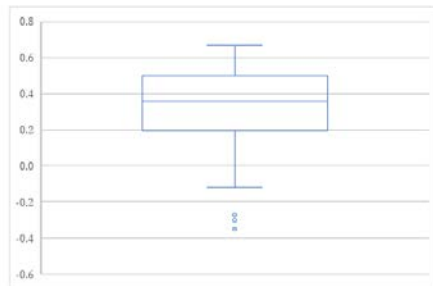


Figure 4. Boxplot of internship scores in hospitality industry (analyzed by TextBlob)

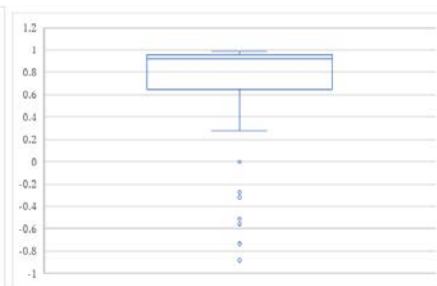


Figure 5. Boxplot of internship scores in hospitality institutions industry (analyzed by VADER)

Figures 6 and 7 respectively show bar graphs of the analysis results obtained using both tools for educational institutions. The analysis results from TextBlob showed 16 positive, 2 neutral, and 3 negative classifications, while VADER results showed 12 positive and 9 negative classifications. The TextBlob results displayed positive sentiments at the highest level, but VADER results showed similar positive and negative sentiment values and did not include any neutral sentiment category.

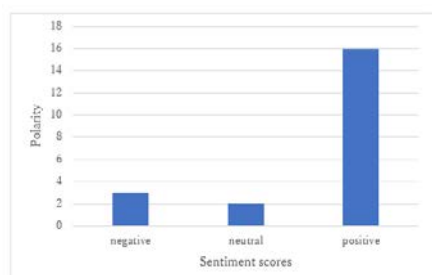


Figure 6. Internship scores in educational institutions (analyzed by TextBlob)

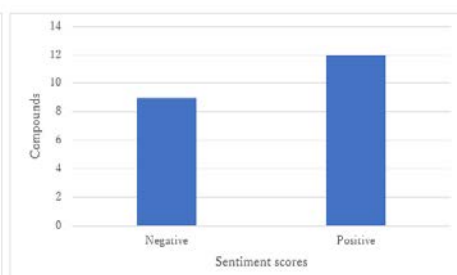


Figure 7. Internship scores in educational institutions (analyzed by VADER)

The boxplot in Figure 8 presents the data that varies moderately between -0.3 and 0.6 with most scores falling between -0.1 and 0.4. The data distribution shows a small positive

skew, while maintaining a stable pattern. The boxplot in Figure 9 demonstrates wider data spread between -0.9 and 1.1, which indicates higher data dispersion. The median value of this dataset reaches 0.35, which indicates the average score is on the positive side. The VADER dataset shows greater spread in its values, while TextBlob dataset maintains its values close to the average.

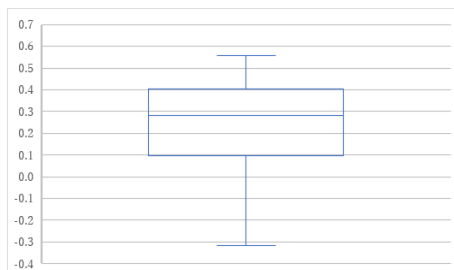


Figure 8. Boxplot of internship scores in educational institutions (analyzed by TextBlob)

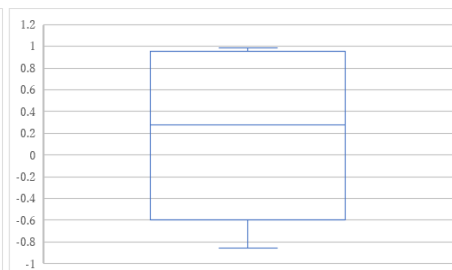


Figure 9. Boxplot of internship scores in educational institutions (analyzed by VADER)

The bar graphs in Figures 10 and 11 display the sentiment scores which both tools generated for other industries. The TextBlob analysis showed 27 positive, 6 neutral, and 3 negative classifications, while the VADER analysis showed 28 positive and 6 negative classifications. Both tools exhibited the same trend, with the number of positive sentiments being remarkably high. However, the VADER results showed no neutral sentiments, while the TextBlob results contained neutral sentiments.

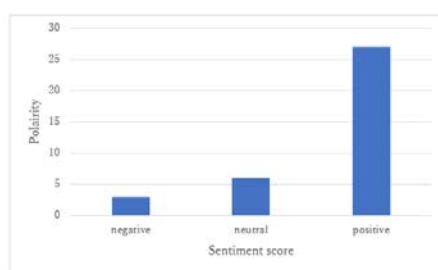


Figure 10. Internship scores in other industries (analyzed by TextBlob)

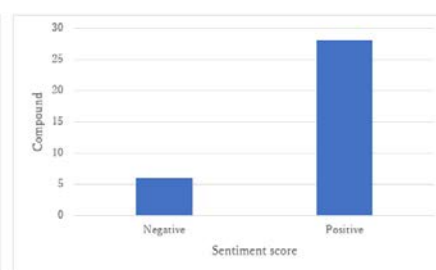


Figure 11. Internship scores in other industries (analyzed by VADER)

The boxplot in Figure 12 displays data that centers around 0.3, while most values fall between -0.3 and 0.6. The interquartile range is narrow, indicating moderate consistency, and there is one outlier near 0.9. This suggests the data are fairly stable with a few unusually high values. The boxplot in Figure 13 displays a median value of 0.7, while showing data points that extend from -0.6 to 1.0. The data points in this set extend over a wider range, which

indicates higher variability. The VADER dataset contains more positive values than TextBlob, while showing increased variability in its responses.

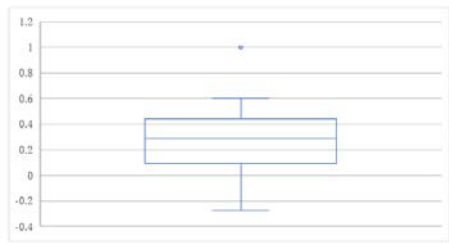


Figure 12. Boxplot of internship scores in other industries (analyzed by TextBlob)

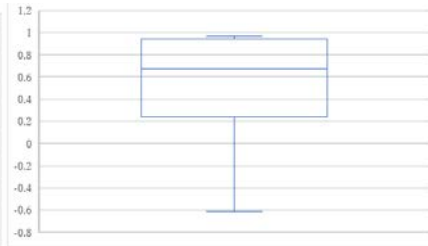


Figure 13. Boxplot of internship scores in other industries (analyzed by VADER)

Next, a Mann-Whitney U test was conducted to compare the sentiment scores obtained from TextBlob and VADER. The U-values from Table 1 led to the following p-values: .00001 for hospitality sector ($Z = 6.72378$), .80258 for educational institutions ($Z = -0.25156$), and .00094 for other industries ($Z = -3.30788$). Given the threshold of $p < .05$, the hospitality sector and other industries showed statistically significant differences in their sentiment scores, while educational institutions did not exhibit any significant difference.

Table 1. Comparison of internship feedback between TextBlob and VADER

		Number of feedback	Sum of ranks	Mean of ranks	U-value
Hospitality	TextBlob	67	6034	90.06	733
	VADER	67	3011	44.94	3756
		Number of feedback	Sum of ranks	Mean of ranks	U-value
Education institutions	TextBlob	35	441	22	231
	VADER	35	462	22	210
		Number of feedback	Sum of ranks	Mean of ranks	U-value
Other industries	TextBlob	21	1489	43.79	330
	VADER	21	996	27.67	612

5. Discussion, Conclusion, and Recommendations

The analysis of three industry datasets through TextBlob and VADER revealed common patterns yet distinct ways these tools evaluate sentiment polarity and intensity. The analysis of hospitality internship feedback showed both tools detected predominantly positive sentiments, which indicated that feedback in this sector had mostly positive comments. The analysis of TextBlob showed 58 positive comments and 5 negative comments, while VADER identified 57 positive comments and 9 negative comments. This alignment suggests that both tools effectively captured the overall optimism within the dataset. However, the boxplots revealed subtle distinctions in sentiment magnitude. TextBlob's results indicate moderate positivity (median ≈ 0.4), reflecting a mix of mildly positive and neutral opinions, whereas VADER's higher median (≈ 0.9) indicates stronger positivity and greater consistency among responses. The analysis shows that VADER detects more intense negative statements which indicate its ability to detect strong emotional language. The Mann-Whitney U test established a statistically significant difference ($p = .00001$) between the two distributions, which proves TextBlob and VADER differ meaningfully in how they score sentiment strength for this domain. This discrepancy stems from differences in how each tool handles the range between negativity and positivity. VADER identified more negative outliers than TextBlob due to its greater sensitivity that resulted in wider polarity spread.

The educational dataset showed TextBlob identifying more positive feedback (positive = 16 and negative=3), but VADER detected a balanced distribution of positive and negative feedback (positive=12 and negative=9). The absence of a neutral category in VADER's output suggests that it tends to polarize sentiments more strongly. Boxplot analysis further highlighted this contrast, showing that TextBlob produced narrower and more stable distributions centered near neutrality, while VADER's results were more dispersed. Despite these visual contrasts, the Mann-Whitney U test revealed no significant difference ($p = .80258$), indicating that statistically both tools interpreted sentiment similarly in this domain. This outcome may stem from VADER's sensitivity in polarizing mildly negative feedback as "negative," in contrast to TextBlob, which is more inclined to treat mildly negative comments as "positive."

The dataset of the other industries showed both tools detecting mainly positive feedback with TextBlob identifying 27 positive comments and 3 negative ones and VADER identifying 28 positive comments and 6 negative ones. The results from TextBlob showed moderate consistency with a median value of 0.3, while VADER results displayed wider variability with a median value of 0.7. The tools agree about positive sentiment but VADER detects emotional intensity at higher levels which results in higher polarity values. The Mann-Whitney U test produced a significant result ($p = .00094$), supporting the visual evidence that the two tools produced distinct score distributions, likely due to fundamental differences in how their sentiment lexicons are scored, even though their polarity frameworks appear similar.

Overall, both TextBlob and VADER identified positivity as the dominant sentiment across all datasets, reflecting generally favorable perceptions within the analyzed feedback. However, VADER consistently generated stronger sentiment with wider variability, which indicates greater sensitivity to emotional tone and intensity. TextBlob, in contrast, tended to generate more moderate and stable scores, likely due to its reliance on averaged polarity without contextual weighting. The Mann-Whitney U test results reinforce these findings: significant differences were found in the hospitality and other industry datasets, but not in the educational dataset. Overall, the analysis implies that the reliability or sensitivity of sentiment analysis tools can vary by context or type of text, so users should be cautious when generalizing the performance of sentiment tools across different industries, as the choice of tool can substantially affect the test results.

The study highlights that sentiment analysis tools can yield different results depending on their design and sensitivity, as VADER tends to detect stronger emotional intensity and more negative outliers, while TextBlob produces more moderate and stable scores. These findings suggest some valuable suggestions. First, it is advisable to use multiple sentiment analysis tools for internship feedback rather than relying on a single tool, as differences between VADER and TextBlob were observed in this study, consistent with the other studies based on the same tools (In & Chanchamnan, 2026; Huda et al., 2025; Dahal et al., 2025). Considering the discrepancies in analysis outcomes commonly observed in the prior and current studies, comparing outputs from different tools can help improve the validity of the analysis. Second, the results should also be interpreted with caution, since sentiment scores highly depends on the characteristics of each tool, particularly in terms of the strength

of positive and negative polarity. The similar trend was also observed in Huda et al. (2025) and Dahal et al. (2025), both of which highlighted the distinctive polarity gaps in VADER compared to TextBlob. Third, extra care should be taken when selecting tools for different internship domains, as performance may vary in the industries, with some tools demonstrating greater sensitivity to contextual nuances and linguistic features, consistent with the recommendation of Dahal et al. (2025) regarding the selection of appropriate tools for different sectors.

Despite the useful insight obtained through this study, limitations still remain in that the results do not apply to other situations but future research should expand datasets, include longer timeframes, and explore additional sentiment analysis tools to enhance generalizability, better evaluate tool performance, and deepen understanding of how sentiment is expressed in internship feedback.

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