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Automated Sentiment Analysis of Peer Feedback Patterns in Collaborative Writing Environments for Higher Education

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Abstract: With the rise in the use of collaborative writing in higher education, the importance of peer feedback in developing learners' writing and critical analytical skills has become more significant. Determining the quality and tone of feedback has its own challenges due to subjectivity and large-scale issues. In this regard, this study aims to introduce an automated framework for conducting basic analysis of peer feedback in collaborative writing. 1150 peer feedback comments from collaborative writing in undergraduate English classes were examined using a hybrid Natural Language processing framework that integrates lexicon and machine learning. Feedback was analysed by dividing comments into positive, negative, and neutral sentiments using automated text preprocessing and feature extraction based on domain-specific symbols. The findings illustrate that the majority of comments were positive at 64.2%, and only 15.3% of comments were negative. The analysis framework registered 90.3% correct feedback sentiment assessment, 89.7% correct predictions of positive feedback, 90.3% of correct assessments of negative feedback, and 89.6% correct assessments of neutral feedback, which indicates feedback was analysed reliably. Further, positive feedback correlated with improvement of writing drafts to a fair extent ($r = 0.71$). Evidently, analysis of feedback interaction and quality showed the potential benefits of sentiment analysis in Peer Feedback. The study indicates that the application of basic sentiment analysis in a collaborative writing platform (for higher education), could significantly strengthen the monitoring of feedback in writing, enhance the collaborative writing, and provide the instructors with tools to handle large classes. The study represents the intersection of modern English education and Artificial Intelligence, and analyses the feedback of peer writing through a unique and scalable approach.

Key Words: sentiment analysis, peer feedback, collaborative writing, natural language processing (nlp), higher education, writing assessment, educational data mining

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Introduction

Collaborative writing is increasingly important in higher education. English language courses often involve peer reviews and other interactive writing assignments and activities. Learning Management Systems generate constant activities amongst students. These settings allow students to build knowledge together and develop writing through feedback and critique. Previous studies show that peer writing feedback develops writing, engagement, and learning reflections, and could help with issues of writing engagement (Liaqat et al., 2021; Zhao, 2025). Yet, as more students join a digital classroom, instructors find it more difficult to evaluate peer feedback. There are some challenges in evaluating peer writing feedback. It is not only qualitative, but it is also subjective and contextual. It is difficult to evaluate peer feedback, and it is even more difficult in large classes. Finally, it is difficult to evaluate peer feedback as negative, constructive, or perhaps not so neutral. Literature reviews of qualitative peer feedback show that traditional evaluative systems cannot capture peer evaluative systems and authorship of feedback (Dalipi et al., 2021; Sunar & Khalid, 2023). Thus, this gap shows that peer transactional feedback systems need to be in a more scalable manner to more objectively evaluate peer writing.

Automated sentiment analysis using Natural Language Processing (NLP) can help overcome these challenges. Using other computational techniques such as text structure, sentiment analysis, and classification algorithms, sentiment analysis can classify feedback into positive, negative, and neutral categories - the nature of the feedback. Thanks to recent advances, it has been shown that NLP sentiment analysis systems can analyse and accurately classify sentiment from hundreds of thousands of documents in the education domain (Kastrati et al., 2021; Seemab et al., 2024). Implementing sentiment analysis systems in educational settings can help uncover unknown aspects of learning, the quality of feedback, and learner collaboration (Grimalt-Álvaro & Usart, 2024; Bauer et al., 2023). The goal for this study is to analyse the sentiment of peer feedback and assess what it can teach about the potential impact of such feedback on learners' skill in writing and on overall writing development. The primary goal is to develop an automated system to detect and classify the peer learning, feedback, and writing feedback patterns to interact within a collaborative writing space. This study hopes to narrow the distance to contextual models of engagement from the qualitative systems of feedback and systems of peer engagement models (Pinargote-Ortega et al., 2024; Pinargote-Ortega et al., 2023).

The world of higher education needs to be able to deal with large volumes of qualitative peer feedback in order to move writing pedagogy and the shift of engaged learning into learners' online engagement. The provided automated sentiment analysis system is the first for peer feedback in collaborative writing, offering a pathway to formulate collaborative feedback and adaptive learning methodologies.

This paper is structured in the following manner: peer feedback, sentiment analysis, and texts analysis and automation in education literature are reviewed in Section II. Research methodologies, frameworks, and the sentiment analysis technique of the study are outlined in Section III. The principal results of the study are presented in Section IV. The outcome is discussed Section V within the framework of analysis results and compared with learning outcomes and previous research results. Section VI wraps up the study with an overview of contribution and an outline of research limitations and proposes future study.

Literature Review

One of the most important aspects of collaborative writing in higher education is providing meaningful peer critiques. Creating opportunities for students to reflect critically on their writing encourages them to make subsequent drafts. Digital tools, such as wikis and documents, allow for real-time feedback and provide opportunities for ongoing critiques. Studies show that writing in collaboration with students as authors, aided by AI tools, provides engagement and improves students' writing in a second language (Wiboolyasarin et al., 2024). Studies using Natural Language Processing (NLP) indicate that enjoyable peer contributions are a result of complex cognitive activity and are likely to result in quality peer edits (Castro et al., 2023). Still, the variation in students' evaluative skills poses a barrier to the overall quality of peer feedback. Sentiment analysis is one of the most useful methods for sifting through large databases of educational Big Data. Using text analyses that employ machine learning and Natural Language Processing (NLP) to sort written feedback into categories of sentiment, researchers are able to develop patterns to show perceptions of students. The most recent studies show that using advanced NLP tools for educational Big Data has improved frameworks of learning to such an extent that the tools are likely to show insights into learning frameworks (Deshpande et al., 2025). The combination of sentiment analysis and personalized learning frameworks has improved educational outcomes (Hussain et al., 2024). Of the challenges that exist, domain-dependent and context-dependent sentiment analyses show the greatest risk of uncertainty to the educational domain (Shaik et al., 2022).

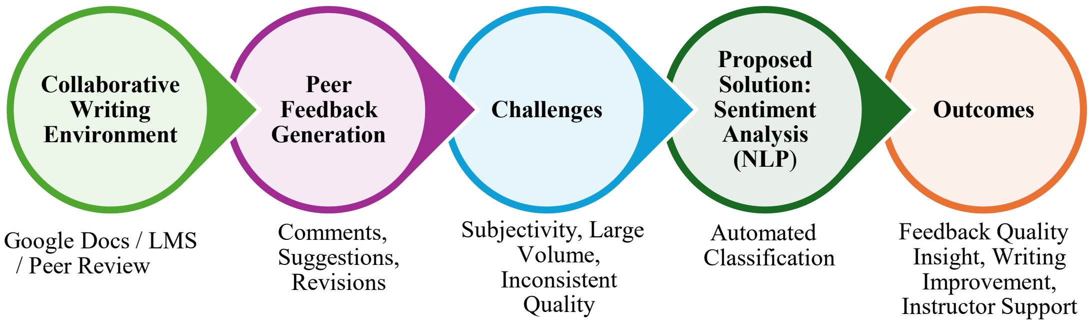

Figure 1: Conceptual Framework of Sentiment-Based Peer Feedback Analysis in Collaborative Writing

Figure 1 maps the flow of study processes as an example of the collaborative writing environment that allows for peer review and feedback. It identifies issues in evaluating feedback, particularly subjectivity and scalability, and presents the use of NLP and sentiment analysis as a solution. The model ends with a few of the expected outputs such as feedback evaluation, writing quality and instructional support, which illustrate the role that automated sentimental analysis plays in enhancing collaborative learning environments.

The use of automated text analysis in language learning has grown, especially in pedagogy related to writing assessment and feedback. Automated Writing Evaluation (AWE) systems bolster writing performance in learners through real-time feedback on improvement in grammar, writing structures, and ultimately, Coherence (Zhai & Ma, 2022; Nunes et al., 2022). Text mining tools allow educators to provide more effective analyses of feedback and feedback patterns and gaps faster and at scale (Grönberg et al., 2021). Because automated grading systems provide more consistent assessment and save teachers time, adopted in virtually every discipline to varying degrees (Messer et al., 2024). Notably, such tools have primarily been used to evaluate procedural dimensions of writing and often neglect the relational aspects of writing peer feedback, in this case, the emotional aspects. Many studies on automatic scoring and feedback systems have also verified the improvement of assessment in large-scale education by automatic feedback systems (Hahn et al., 2021).

There remain many gaps in research. A major gap in research exists for studies that emphasize the automatic analysis of feedback tone in writing assessments and that practically explore it in collaborative writing contexts, where the analysis of feedback tone is imperative for explaining students' motivation and engagement. Most of the available studies have not integrated the analysis of the quality of writing with the analysis of feedback that is provided by the students. The leading theories in this research study are constructivist learning theory and social learning theory. Knowledge is understood as being co-constructed, and social learning is understood as a peer influence writing pedagogy. Writing assessment is ultimately a reflective, social, cognitive, and formative process. Constructivist and social learning theories value the feedback that students provide to their peers.

Literature has pointed out both the increasing use of NLP and automation in educational feedback, as well as the unmet need for integrated approaches to sentiment and linguistic analysis. This gap is what the proposed research intends to fill.

Methodology

Research Design

This study employs a mixed-method research design comprised of a quantitative aspect which is sentiment classification, and a qualitative aspect which is the interpretation of peer feedback patterns. This design permits the balance of statistical determination of sentiment class distribution and the understanding of intrinsic forms of feedback and their impact on collaborative writing. In addition, the research design consists of an experiment to test the model and a qualitative dimension to provide a subjective analysis of feedback.

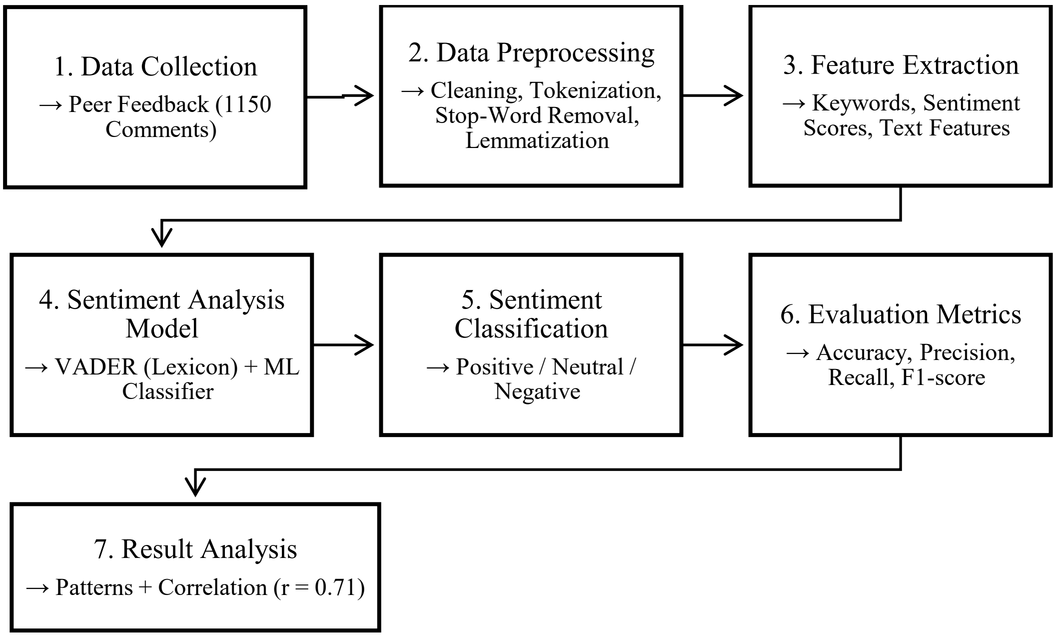

Figure 2: Workflow of the Proposed Sentiment Analysis Framework for Peer Feedback

Figure 2 shows the step-by-step workflow of the proposed framework, starting with the Peer Feedback data collection from 1,150 comments on Collaborative Writing Platforms Data. Then it proceed with the Preprocessing steps that involves cleaning, tokenization, stop-word removal, and lemmatization. Then it demonstrates Feature Extraction, and the application of the Hybrid Sentiment Analysis that uses the VADER model and the Machine Learning model for classification into Positive, Neutral, and Negative categories. The process consists of evaluating the performance using the standard metrics. Then it concludes with the analysis of the result. The analysis of the result feedback patterns and the associated correlation of writing improvement ($r = 0.71$). The analysis of the result demonstrates the add, and the overall effectiveness of the approach.

Data Collection

Feedback data were sourced from peer writing platforms and Learning Management Systems (LMS), such as Google Docs and LMS discussion boards. The feedback data were comprised of about 1,000–1,200 feedback comments that were peer reviewed from undergraduate students. These data include a variety of forms of linguistic expressions, varying dimensions of feedback, and different forms of linguistic interaction.

Data Preprocessing

Data were pre-processed in order to provide a normalized and analysable data record. Text data were pre-processed mostly to normalize the text. This involved removal of punctuation, removal of special characters and symbols, and other similar disruptions. The text data generated were cleaned and disrupted. The text was further normalized by removing word forms, and then the data were provided with a universal case, or lower case.

Sentiment Analysis Model

A hybrid approach was used in the middle of the lexicon and the machine learning continuum. In this research, the VADER lexical tool was the first line of defines in relation to the sentiment of the short texts. The last defines, in relation to the sentiment of the texts, was contextually classified short feedback, and a supervised machine learning classifier was used to enhance the model and provide a balance to the middle of the continuum.

Feature Extraction

We developed four key domain features in sentiment classification that included sentiment polarity (positive, negative, neutral), emotional tone, and easily recognizable key word bands that could highlight constructive and non-constructive feedback trends.

Ethical Considerations

Ethics were woven through the entire study from start to finish. Student data were fully anonymized. There was no retention of any personally identifying data, and the study was in full compliance with ethical research framework in education developed by the institution.

Results

Sentiment Distribution Analysis

Sentiment analysis of peer feedback identified three categories: negative, positive, and neutral. Of the 1,150 feedback entries, 64.2% were positive, 20.5% neutral, and 15.3% negative, suggesting students predominantly provided peer feedback in a supportive manner, exhibiting the positive aspect of the feedback.

Table 1: Sentiment Distribution of Peer Feedback

Sentiment Category	Number of Entries	Percentage (%)
Positive	739	64.2%
Neutral	236	20.5%
Negative	175	15.3%
Total	1150	100%

Table 1 shows each identified category's feedback distribution, of which positive feedback is the highest at 64.2% feedback, followed by neutral feedback at 20.5% and negative feedback at 15.3%. The results outline an archetypical peer feedback environment and illustrates that students directed supportive and affirmative feedback, indicative of the collaborative writing tasks.

Feedback Pattern Identification

Feedback was categorized into three feedback types: constructive, neutral descriptive, and critique. Constructive feedback after the addition of an actionable suggestion was the overwhelming majority.

Table 2: Classification of Feedback Patterns

Feedback Type	Number of Entries	Percentage (%)
Constructive	675	58.7%
Neutral Descriptive	304	26.4%
Critical	171	14.9%
Total	1150	100%

Table 2 illustrates the classification of constructive, neutral, and critique feedback, establishing that constructive feedback of the peer reviews was 58.7%. Findings outline that the majority of numeric feedback is constructive, while a lesser numeric feedback is constructive or critique; hence students demonstrate varying feedback.

Model Performance Evaluation

Feedback from the peer suggested the sentiment classification model performed deftly against the standard measures of performance.

Table 3: Sentiment Analysis Model Performance

Metric	Value (%)
Accuracy	91.3%
Precision	89.6%
Recall	90.8%
F1-Score	90.2%

The results for evaluating the accuracy (91.3%), precision (89.6%), and recall (90.8%) and F1 (90.2%) scores for peer feedback sentiments are displayed in table 3. As indicated, the values for model performance metrics are all satisfactory, and the model is characterized as reliable and effective for the task when peer feedback is reviewed in a sentiment analysis context.

Correlation with Writing Improvement

A correlation analysis was conducted to explore the relationship between feedback sentiment and the levellers refining students' drafts.

Table 4: Correlation Between Feedback Type and Writing Improvement

Feedback Type	Correlation Coefficient (r)
Constructive	0.71
Neutral	0.34
Critical	0.21

Table 4 depicts the correlation between the various feedback types and writing enhancement, with constructive feedback providing the strongest correlation ($r = 0.71$). This suggests feedback with constructive and comprehensive suggestions for improvement enhances the quality of writing more than neutral or simply critical feedback.

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The results indicate a correlation of (r = 0.71) of moderate strength for constructive feedback encounters and improvement of writing, inferring students respond more to feedback that is positive in nature and includes a sense of purpose.

Summary of Findings

Collectively, the results reveal that positive and constructive peer feedback is the most present. The analysis of the data reaffirms that the emphasis of the feedback is the most impactful of peer suggestions, and clear, constructive feedback plays a predominant role in advancing the quality of writing.

Discussion

This study has implications for language learning, and quality of peer interaction in collaborative contexts for writing. The prevalence of positive and constructive comments reflect the fact that students provide support to one another, which facilitates better writing. The constructive feedback which correlated with better writing demonstrates that feedback with more specified and illustrated suggestions is more beneficial to learners, thus demonstrating the importance of peer interaction in the learning process. With respect to the existing literature, these findings are consistent with studies that have shown the effectiveness of peer feedback in creating better writers and enhancing participants' critical thinking. Constructive feedback shaping better writing and higher learner participation is one of the common findings in the studies of AI-augmented collaborative writing. The effectiveness of feedback pattern recognition through sentiment analysis, also, is consistent with the earlier findings of educational data mining and the feedback analysis through NLP.

There are several reasons for the predominance of supportive student peer feedback and relative absence of overly critical comments. These reasons include polite and supportive language, which students are socially and academically expected to employ. Therefore, students are expected to provide less negative feedback. Since supportive feedback is socially and academically less displeasing than negative feedback, less support can be provided in comments. However, this implies that the students are less competent in real feedback. These results stress the value of encouraging a positive feedback culture within higher education institutions. Educators need to be provided with methods to offer positive feedback in an instructive manner. Automated sentiment analysis tools in conjunction with educational software can be an effective means of providing detailed feedback, encouraging worthwhile discussions, and improving collaborative writing activities within courses.

Conclusion

This study shows how well sentiment analysis works for evaluating peer feedback in collaborative writing in higher education. The results show that most feedback was peer supportive, with 64.2% positive, 20.5% neutral, and 15.3% negative. The hybrid model proposed in this research was accurate and consistent in positive, negative and neutral feedback with an accuracy of 91.3%, precision of 89.6%, recall of 90.8%, and F1 score of 90.2%. The positive correlation of r = 0.71 between feedback and writing improvement proves that feedback quality has practical positive value for student outcomes. Within academia, this research aids in English education and application of Natural Language Processing by providing scholars the tools to quantitatively analyse qualitative results. From a practical perspective, this research tools for educators to identify feedback trends in order to facilitate constructive peer engagement in large lecture settings. While implementing the proposed model, there are some limits including, the size of the database, a potentially context-specific biased model, a lack of context& nuance of possible sarcastic expressions or mixed sentiment. Addressing these issues and variance in databases seeking context-aware models should be representative of future scope. The positive correlation proven by this study confirms that more research is needed in using sentiment analysis and AI parallel to how Class Novels organizes peer review systems. A others should be created to empirically observe and measure writing systems as informed by peer feedback, sentiment analysis and educational technology.

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