Exploiting Aspect-Based Sentiment Analysis on Vietnamese Learner Feedback: Dataset Foundation and Applications for E-learning System Enhancement

Le Thi Thu Hien
Faculty of Software Engineering
University of Information Technology
Ho Chi Minh City, Vietnam
21522059@gm.uit.edu.vn

Mai Dinh Khoi
Faculty of Software Engineering
University of Information Technology
Ho Chi Minh City, Vietnam
21522059@gm.uit.edu.vn

Nguyen Thi Thanh Truc
Faculty of Software Engineering
University of Information Technology
Ho Chi Minh City, Vietnam
trucntt@uit.edu.vn

***Abstract* — In the context of the rapid and irreversible development of online education, understanding learners' emotions and opinions has become one of the key factors in improving the quality of teaching and learning. However, most current analytical systems remain limited to assessing overall sentiment, thereby overlooking the diversity and complexity embedded in learners' feedback on specific aspects of a course. Aspect-Based Sentiment Analysis (ABSA) outperforms traditional methods by simultaneously identifying both the sentiment and the specific target being referred to. This enables a more detailed and nuanced understanding, laying the foundation for more effective assessment and personalization systems in online learning environments.**

This paper proposes a learner-centered approach by applying ABSA to analyze student feedback in Vietnamese E-learning contexts. We introduce *ViLearn-ABSA*, a domain-specific dataset constructed with annotated labels across seven educational aspects: Instructor, Content, Assignments & Practice, Materials, Pace, Technology, and Others. Based on this dataset, deep learning models have been fine-tuned and evaluated to effectively extract sentimental information. Experimental results demonstrate high accuracy in identifying the relationships between sentiments and aspects, thereby contributing to supporting instructors in managing, adjusting, and personalizing learning experiences, ultimately enhancing learning quality.

This work not only contributes a valuable resource to the Vietnamese NLP community but also affirms the potential of ABSA as a powerful tool in educational research and system development, aiming toward user-centered learning experiences.

Keywords: E-learning; Aspect-Based Sentiment Analysis (ABSA); Natural Language Processing (NLP); Student Feedback; Course Improvement.

I. Introduction

In the context of global digital transformation in education, E-Learning is increasingly affirming its crucial role, especially in addressing challenges such as the shortage of in-person teachers and the unequal distribution of high-quality educational resources, including disparities in educational infrastructure and teaching quality between urban and remote areas [1]. Particularly after the COVID-19 pandemic, online learning has gained widespread popularity, with the global market reaching USD 342.4 billion in 2024 and projected to grow to USD 682.3 billion by 2033, at a compound annual growth rate of approximately 8% [2]. This robust growth is largely driven by the increasing demand for remote learning solutions, as individuals face constraints in time, workload, and financial resources. Online learning addresses these challenges by offering flexible access, cost efficiency, and personalization.

However, ensuring teaching quality and learning experience in digital environments remains a pressing challenge due to limitations in direct interaction between instructors and learners. Teachers are unable to observe learners' facial expressions, tone of voice, or physical cues to gauge how they feel during the course and must rely solely on written feedback. Therefore, analyzing learners' written responses plays a critical role in gaining deeper insights into their emotional states. While qualitative feedback from learners is a valuable source of data, manually processing a large volume of comments is impractical and inefficient. Moreover, current evaluation systems primarily focus on teaching effectiveness or platform performance, while overlooking essential feedback and expectations from the learners themselves [1].

To address these limitations, Natural Language Processing (NLP) techniques—particularly Aspect-Based Sentiment Analysis (ABSA)—have emerged as effective tools for extracting deeper emotional insights from learner feedback. Unlike traditional sentiment analysis methods that merely classify overall sentiment, ABSA enables the identification of sentiment polarity (positive, negative, neutral, or mixed) associated with specific aspects mentioned in the text. This allows for a more comprehensive and detailed understanding. Advanced language models such as phoBERT have demonstrated high effectiveness in performing this task.

This study is conducted to address the significant gap in assessing the quality of online courses from the learner's perspective, an essential factor in improving and personalizing digital educational experiences. Rather than relying solely on aggregated metrics such as average ratings or course completion rates, this research focuses on exploring the depth of learner feedback through aspect-based sentiment analysis (ABSA). Specifically, a specialized Vietnamese ABSA dataset has been constructed from actual student comments in online learning environments, with sentiment labels annotated for specific aspects such as instructor quality, lecture content, materials and exercises, pace, technology, and others. This effort aims to standardize Vietnamese learner feedback data to support AI research in education.

Based on this dataset, modern language models such as phoBERT have been fine-tuned to better capture semantic nuances in online educational contexts. Sentiment analysis is conducted not only at the sentence level but also at the aspect level, aiming for higher accuracy in identifying learners' attitudes—positive, negative, neutral, or conflicting components. This marks an important step toward developing automated systems capable of more nuanced understanding of learner feedback, rather than limiting to overall sentiment.

Building on the outputs of the ABSA system, the study further develops an E-learning platform integrated with the capability to visualize feedback statistics by aspect. This system not only provides a comprehensive view of course quality but also enables instructors to quickly identify strengths and areas for improvement, thereby making informed adjustments to enhance learners' experiences. Instead of relying on intuition or superficial quantitative metrics for content development decisions, instructors can now rely on in-depth sentiment analysis automatically extracted from learners' actual feedback, the most direct source reflecting the realities of the teaching and learning process

II. THEORETICAL FRAMEWORK

A. *Sentiment Analysis in the E-learning Context*

In the context where E-learning is increasingly becoming a popular and flexible learning method, the need to enhance training quality through listening to and analyzing learner feedback has become more pressing than ever. Such feedback not only reflects the overall level of satisfaction but also contains a wealth of detailed information about actual learning experiences—if analyzed in depth. However, most current evaluation systems remain at a general level, focusing on measuring the overall sentiment of learners without identifying specific evaluations related to individual components of the courses such as the instructor, lesson content, exercises, teaching pace, or technology. This lack of granularity has limited the ability to improve courses in a focused and effective manner.

Against this backdrop, Natural Language Processing (NLP) techniques—especially Aspect-Based Sentiment Analysis (ABSA)—have emerged as a promising solution. ABSA enables systems not only to identify learners' emotional attitudes but also to clearly determine which specific aspect those attitudes are directed toward within the feedback. Instead of a generic comment like "the course is very good," an ABSA model can analyze more deeply and recognize that "the instructor explains clearly" is a positive opinion directed at the instructor aspect, while "the exercises are too difficult" is negative feedback related to the exercises. Thanks to this capability, ABSA offers a new approach to automatically analyzing learner feedback more accurately and usefully, thereby supporting instructors in improving their teaching content based on real-world data rather than subjective guesswork [1][6].

B. *Aspect-Based Sentiment Analysis (ABSA)*

One of the major challenges in analyzing learner feedback in E-learning environments lies in the multidimensional and contextual nature of natural language. Learners do not merely express general emotions but often provide detailed, layered remarks, in which a single comment may simultaneously convey different emotional attitudes toward different aspects. This requires a high-resolution analysis approach, something that traditional sentiment analysis methods still lack. While these models primarily operate at the document level, often leading to generalized and imprecise results, ABSA stands out due to its ability to dissect and locate sentiment at specific content focal points. With the capacity to recognize both "what is being talked about" (the aspect) and "how the sentiment is expressed" (the polarity), ABSA becomes a particularly suitable tool for processing the complex feedback structures commonly found in education.

Going beyond mere sentiment classification, ABSA offers the potential to model learners' perceptions in a way that more closely reflects their real experiences. When a learner says "Nội dung bài học thú vị, nhưng tốc độ giảng quá nhanh" (The lesson content is interesting, but the teaching pace is too fast), the issue is no longer about whether the sentence is positive or negative, but rather that the learner is experiencing a somewhat positive perception of the content while facing a difficulty with the pace. These micro-level differences are precisely the valuable insights that instructors need to capture. ABSA, as a core technique in Natural Language Processing (NLP), helps "translate" learners' free-form feedback into clear and structured information. In other words, instead of storing feedback as disconnected textual comments, ABSA enables the system to understand what the learner is referring to (e.g., instructor, exercises, pace…) and how they feel about each part (positive, negative, conflicting, or neutral) [1][15]. As a result, learners' opinions are no longer vague and hard-to-summarize remarks, but become data that can be categorized, compared, and visualized by specific course components. This allows instructors to move away from subjective guesses and instead make appropriate, precise, and effective adjustments for each part of the course based on concrete evidence drawn from the learners' own comments.

C. *Aspect Taxonomy and Sentiment Definition*

Based on the classification system proposed by Zeng et al. [1] and the Quality Matters (2019) [4] online course evaluation framework, this study identifies seven core aspect groups that frequently appear in learner feedback in E-learning. These include Instructor, Content, Exercises & Practice, Materials, Pace, Technology, and a combined category named Other. This clear categorization helps guide the process of aspect-based sentiment labeling and analysis in a systematic and consistent manner, while also accurately reflecting the elements that directly affect the learner's experience.

In parallel, the emotion system is specifically defined into four types [1][6][15]: Positive, Negative, Neutral, and Conflicted - each representing a different shade of the learner's perception. Positive feedback typically expresses satisfaction, motivation, or appreciation, such as "Giảng viên rất nhiệt tình" (The instructor is very enthusiastic) - indicating recognition of teaching quality. In contrast, negative feedback reflects disappointment or dissatisfaction, such as "Tài liệu không rõ ràng" (The materials are unclear), showing a barrier to accessing content. Neutral feedback consists of descriptive remarks that do not convey clear attitudes, for example, "Bài học dài 30 phút" (The lesson lasts 30 minutes) - which provides objective information without expressing any emotion. Most noteworthy is the conflicted emotion class, where the learner simultaneously expresses both appreciation and dissatisfaction about the same aspect within a single comment, for instance, "Nội dung hay nhưng khó tiếp cận" (The content is good but hard to access). This emotion type is particularly important in online learning environments, where learning experiences are easily affected by multiple opposing factors. According to Hoang et al. [15], accurately identifying and handling conflicted emotions not only helps reflect learners' perceptions more truthfully but also plays a vital role in detecting underlying issues that need improvement in the course.

D. Data Augmentation and the PhoBERT Model

Despite significant advances in aspect-based sentiment analysis (ABSA), one of the major challenges current ABSA systems faces is label imbalance in learner feedback datasets - particularly for less frequently occurring sentiment classes such as conflicted or neutral. Although these classes are not dominant, they often carry highly valuable information, reflecting complex psychological states or objective observations that can significantly influence learning outcomes. To address this issue, the study applies several data augmentation techniques, including Random Oversampling, AugSBERT, and EDA (Easy Data Augmentation). These methods not only help rebalance the training dataset but also enhance linguistic diversity, thereby improving the model's generalization capacity for handling rare linguistic patterns.

From a modeling perspective, this study adopts PhoBERT - a pre-trained Vietnamese language model based on the RoBERTa architecture - as the backbone of the ABSA system. PhoBERT has demonstrated state-of-the-art performance in various Vietnamese NLP tasks, including aspect-based sentiment analysis. Specifically, on the benchmark VLSP 2018 dataset, PhoBERT achieved an F1-score of 83% in aspect detection and over 77% in the combined task of aspect detection and sentiment classification [12]. These results highlight PhoBERT's strong potential in processing complex and context-rich Vietnamese sentence structures.

In this study, PhoBERT serves as the core model for the Vietnamese ABSA system, enabling deep contextual and structural understanding of learner feedback. The goal is to build a sentiment-aware evaluation system that is flexible, accurate, and culturally–linguistically aligned with the Vietnamese E-learning context.

III. Research Methodology

A. Data Collection and Dataset Construction

1) Data Sources

In this study, the dataset was collected from widely used online learning platforms such as YouTube, Udemy, and Coursera - platforms where learners frequently leave comments and reviews upon completing a course. These feedback entries are spontaneous and authentic, directly reflecting the learners' actual experiences across multiple aspects, including instructor, content, materials, pace, and the practicality of assignments. This approach ensures that the input data holds high practical value and remains closely aligned with the real-world analytical needs of digital education environments.

2) Data Annotation

To train the model, the collected data must first be manually annotated with appropriate labels. Each feedback entry was labeled along two dimensions: aspect and sentiment polarity. For aspect annotation, responses were categorized into seven major groups: Instructor, Content, Assignment & Practice, Material, Technology, Pace, and a miscellaneous group labeled Other to cover outlier factors. Regarding polarity, each comment was classified into one of four categories: Positive (3), Neutral (2), Negative (1), and Conflicted (4) - with the latter capturing internal contradictions within a learner's judgment.

To ensure objectivity and reliability in the annotation process, two independent annotators were employed. Inter-annotator agreement was measured using Cohen's Kappa coefficient [16], yielding a score of k = 0.957. According to the interpretation scale by Landis & Koch (1977), this indicates "almost perfect agreement," thereby affirming the high reliability and consistency of the labeled training dataset.

$$Po = \frac{12290}{12592} \approx 0.976$$

$$Pe = \sum_{i=0}^{k} \frac{niA}{N} \cdot \frac{niB}{N} \approx 0.441$$

$$K = \frac{Po - Pe}{1 - Pe} \approx 0.957$$

3) Data Preprocessing

After the annotation process was completed, a final consensus label was assigned to each feedback instance for model training. The input data then underwent a preprocessing pipeline to ensure consistency and reduce linguistic noise. Specifically, all text was normalized to UTF-8 encoding to eliminate compatibility issues that could cause errors during training.

Common non-standard abbreviations and spelling errors in Vietnamese - such as "sv" (short for sinh viên – student) or "bt" (bài tập - assignment) - were expanded to their full canonical forms. To preserve the semantics of fixed multi-word expressions (e.g., giảng viên - instructor, tốc độ học - learning pace), the research team employed the VnCoreNLP library to segment and join such phrases into unified tokens (e.g., "giảng_viên"). This transformation enhances the model's ability to capture context-aware word relationships more effectively.

Additionally, expressive elongated characters (e.g., hayyyyy quáaaa - "sooo good") were normalized to their base forms (e.g., hay quá) to reduce noise and prevent the model from learning misleading patterns that lack semantic significance.

4) Dataset Statistics

The dataset constructed in this study comprises a total of 10,077 learner feedback entries, collected from various E-learning platforms to ensure diversity and real-world representativeness of the online learning experience. In terms of sentiment distribution, positive feedback accounts for 59.56%, indicating that the majority of learners reported a favorable experience with online courses. This is a promising signal, suggesting that the core components of these courses generally meet learner expectations.

On the other hand, negative feedback constitutes 27.52%, a non-negligible proportion that highlights persistent issues requiring further improvement. Notably, conflicted sentiment, which comprises 9.84% of the dataset, reveals the nuanced and ambivalent perceptions learners often hold—where a single comment may simultaneously express praise and criticism toward a specific aspect of the course. This sentimental class is particularly information-rich, offering valuable insights into balanced and targeted course enhancements.

Finally, the neutral class accounts for only 3.07%, suggesting that most learners prefer to express clear evaluative opinions rather than providing purely descriptive or emotionally neutral feedback.

Table III-1: Data analysis by aspect

Instructor	23 %
Content	79 %
Materials	4 %
Exercises & Practice:	5 %
Technology	6 %
Pacing	3 %
Others	5 %

B. Data Imbalance Handling

Analysis of data distribution shows a clear imbalance between sentiment and aspect classes, in which feedback related to technology or having neutral and conflicted sentiments accounts for a very small proportion compared to the other groups. This imbalance can lead to biased learning, reducing the model's ability to accurately identify infrequent but information-rich cases, such as conflicted emotions—which often carry nuanced reflections involving both praise and criticism in the same comment.

To address this issue, the study implemented three techniques for handling imbalanced data: Random Oversampling (increasing the number of minority class samples by duplicating existing ones), Easy Data Augmentation – EDA (applying simple linguistic operations such as synonym replacement, word order swapping, random insertion or deletion), and Aug-BERT (generating new texts based on deep language models).

Through experimentation and comparison, Random Oversampling demonstrated superior performance, helping improve both accuracy and F1-score. Therefore, this method was selected as the main solution in the training data processing pipeline for the ABSA system.

C. Model and Training Configuration

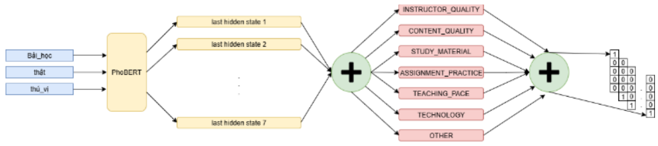

Figure III-1: Overall architecture of the proposed PhoBERT-based multi-aspect sentiment analysis model for Vietnamese learner feedback.

In this study, we selected PhoBERT-base—a pre-trained language model specifically designed for Vietnamese and developed based on the RoBERTa architecture—as the backbone for the Aspect-Based Sentiment Analysis (ABSA) task. To optimally leverage the multi-level semantic representations from the pre-trained model, we extracted and aggregated features from the last seven hidden layers of PhoBERT.

Model architecture is designed following the multitask learning paradigm [17], in which a separate output branch is learned for each specific aspect. Specifically, we define seven core aspects relevant to learning quality in E-learning environments, including: INSTRUCTOR_QUALITY, CONTENT_QUALITY, STUDY_MATERIAL, ASSIGNMENT_PRACTICE, TEACHING_PACE, TECHNOLOGY, and OTHER. Each aspect is mapped to an independent task-specific classifier, where sentiment labels are assigned from the set {positive, negative, neutral, conflicted, not mentioned.

The final output is a 35-dimensional binary vector, representing the combination of 7 aspects and 5 sentiment classes, as illustrated in Figure III-2.

IV. Results and Discussion

This study lays the foundation for a novel approach to Aspect-Based Sentiment Analysis (ABSA) in the context of Vietnamese E-learning, through the construction of a domain-specific dataset named ViLearn-ABSA. This dataset is designed to authentically reflect learner feedback in Vietnamese online education environments, with a structured annotation schema that aligns closely with the standard ABSA task, including well-defined aspect categories and sentiment labels.

In the experimental phase, the study focuses on evaluating the impact of various data imbalance handling techniques across two core subtasks: aspect detection and aspect-based sentiment classification. The compared approaches include a baseline model without imbalance treatment, Random Oversampling, Easy Data Augmentation (EDA), and Aug-BERT.

The results reveal that Random Oversampling, despite its simplicity, yields significant improvements - particularly in the Aspect Sentiment Classification task: the Macro F1-score increases from 0.6205 to 0.6706, and Recall improves from 0.6278 to 0.6771, indicating better label coverage and enhanced robustness of the model across underrepresented sentiment classes.

Table IV-1: Table of data growth categorized by method

Task	Method	Accuracy	F1-score (Macro)	Recall	Precision
Aspect	Base model	0.9784	0.9634	0.9634	0.9635
	Random Oversampling	0.9791	0.9643	0.9639	0.9649
	Easy Data Augmentation (EDA)	0.9786	0.9635	0.9632	0.9638
	Aug-BERT	0.9790	0.9646	0.9651	0.9641
Aspect – Emotion	Base model	0.9532	0.6205	0.6278	0.7720
	Random Oversampling	0.9570	0.6706	0.6771	0.7969
	Easy Data Augmentation (EDA)	0.9549	0.6489	0.6281	0.8257
	Aug-BERT	0.9576	0.6325	0.6290	0.7942

The experimental results demonstrate the model's notable capacity in identifying positive sentiment, which constitutes the majority of real-world feedback in E-learning settings. This strength reflects the psychological tendency of learners in digital environments, where positive opinions are often expressed more explicitly and consistently.

However, the model still struggles to accurately classify neutral or conflicting feedback, especially in less frequent aspect-sentiment pairs, such as content_quality–neutral or other–conflict. These limitations not only highlight the current model's challenges but also underscore a common issue in natural language processing tasks dealing with imbalanced datasets: the inability to effectively learn from low-frequency labels.

The presence of such shortcomings, paradoxically, attests to the realistic nature of the ViLearn-ABSA dataset. The model's performance degradation on rare labels suggests that the dataset has not been overly sanitized or biased, thereby preserving the diversity and authenticity of learner feedback. This opens promising directions for further research to enhance model performance in underrepresented classes. One potential avenue involves developing semantically grounded data augmentation techniques, rather than relying solely on lexical operations like synonym replacement or naive duplication. By generating synthetic feedback that closely mirrors real-world discourse, the model can be exposed to richer learning signals for rare label instances.

Additionally, the integration of label-specific attention mechanisms could offer a viable solution. Current architectures tend to distribute attention uniformly across all classes, which is suboptimal in severely imbalanced ABSA scenarios. A more guided attention strategy may enable the model to focus better on informative, low-frequency signals that are critical for nuanced classification.

Despite certain limitations compared to commercial systems trained on large, balanced, and heavily fine-tuned datasets, this research has made several key contributions. First, ViLearn-ABSA is the first ABSA dataset specifically developed for Vietnamese E-learning, with high-quality annotations validated by a Cohen's Kappa score of 0.957—a strong indicator of consistency and reliability in the labeling process. Second, the study clearly demonstrates the impact of data imbalance on model performance, while proposing practical and reproducible solutions that can be readily applied in similar contexts within the Vietnamese NLP community.

Taken together, ViLearn-ABSA is not only a new academic resource for Vietnamese language processing, but also serves as a critical foundation for advancing fine-grained analysis of learner feedback in online education systems

V. CONSLUTION

This study marks a significant turning point in the application of Aspect-Based Sentiment Analysis (ABSA) to the Vietnamese E-learning domain an increasingly expanding educational space that still faces a severe lack of native-language processing tools. By constructing the ViLearn-ABSA dataset with fine-grained aspect and sentiment annotations, we have not only provided a new public resource for the research community but also introduced a reference standard for how learner feedback is shaped and expressed within the context of online education in Vietnam.

More importantly, the experimental findings reveal that data imbalance an inherent limitation in real-world learner feedback has a significant impact on model performance. Applying Random Oversampling not only led to measurable gains in F1-score but also helped restore semantic coherence across high-frequency aspect-sentiment pairs. These outcomes underscore the value of strategically calibrating data distributions to strengthen model reliability, even in imbalanced environments. Building upon these findings, the study demonstrates the practical viability of harmonizing large-scale pre-trained language models with context-aware data adjustment techniques in the domain of educational NLP.

We argue that ViLearn-ABSA is not merely an academic artifact, but a foundational step toward building intelligent educational platforms capable of understanding learners' natural language as a prerequisite for personalized learning experiences. Future research directions may include expanding the dataset, integrating adaptive attention mechanisms for low-frequency labels, and incorporating real-time feedback systems. These are key to realizing the broader vision in which artificial intelligence not only reads language but also comprehends educational sentiment in localized contexts.

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