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Sentiment Analysis of Students' Feedback Using the VADER Model for Teaching Process Assessment

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ABSTRACT

The evaluation of the teaching activity by students serves as a way of assessing its quality and efficiency in higher education institutions. The objective of this type of evaluation is to provide valuable insight into the quality of the teaching act and into the areas in which the teaching practices might be improved both by teachers and other interested parties. This paper presents an approach to the analysis of sentiment expressed in student evaluations based on a mixed evaluation model with general qualitative criteria and using a general sentiment analysis model, the VADER (Valence Aware Dictionary and sEntiment Reasoner) model. The article examines the extent to which such a general model for sentiment analysis can be used, without further modifications, for sentiment analysis in this particular domain.

1. Introduction

The assessment of student satisfaction has evolved significantly in recent decades, combining various methods to obtain a more complete picture of the educational experience.

Traditionally, quantitative evaluations such as questionnaires with Likert scale responses have been used to measure student satisfaction. These tools allow structured data collection and statistical analysis of results (Richardson, 2005). However, recent research points out that quantitative methods can be limiting when they are not accompanied by an understanding of the qualitative context (Takona, 2023). Common criticism is represented by the fact that they may miss the complexity of the student experience, limiting the ability to identify the reasons behind satisfaction scores.

A second approach in the domain-specific literature has focused on qualitative methods, such as interviews and focus groups, which can provide a deeper insight into students' perceptions, capturing certain nuances of their experiences (Creswell & Plano Clark, 2011). A recent study demonstrated that using qualitative methods in combination with quantitative methods can reveal hidden factors that influence satisfaction, such as the quality of interaction with teachers and the relevance of course content to students' career goals (Das et al., 2023). Collecting and analyzing qualitative data requires more resources, and results can be difficult to interpret and generalize to the entire student population.

However, mixed-method approaches have become more popular, offering a way to combine the advantages of quantitative and qualitative methods (Creswell & Plano Clark, 2022). Studies in recent years emphasize the importance of this approach for a more complete assessment of student satisfaction, allowing a more detailed analysis of the data and a deeper understanding of the educational context (Takona, 2023; Das et al., 2023).

Although the evaluation of the educational process is a current practice for universities, the use of its results has not been maximized, especially in the case of evaluations with open qualitative questions. Analyzing qualitative evaluations can be manageable when the data volume is small, but as the volume of data increases, manual analysis becomes difficult. An appropriate method is thus needed to analyze open-ended responses from such assessments. One of the methods that can be used for this purpose is text mining (Gottipati et al., 2017). Text mining, including sentiment analysis, has been used more frequently in marketing and social media to extract insights hidden in customer opinions/comments/ratings. The application of text mining and sentiment analysis techniques in the qualitative evaluation of the educational process is more recent, and studies show that the use of one technique or the other for sentiment analysis in this field depends on the objectives pursued (Ulfa et al., 2020).

The results obtained from these evaluations are used to improve the existing educational process so that the learning objectives are achieved. Gottipati et al. have proposed a framework that illustrates how

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qualitative and quantitative feedback can be used to make informed decisions about improving teaching, learning and curriculum processes.

In this article, we will use a general model, the VADER model, to analyze students' sentiments, expressed in general open-ended questions in a mixed evaluation questionnaire, in order to determine their level of satisfaction with the educational process. The second objective of this research is to determine the extent to which such a general model is adequate for sentiment analysis in this domain.

2. The proposed evaluation model

The proposed mixed evaluation model contains general qualitative questions by means of which students can say what they liked, what they didn't like, and what they think could have been better in the evaluated courses. Three quantitative evaluation criteria are added to these general qualitative criteria, namely: the grade for the course content, the grade for the laboratory content, and the grade for the teacher's teaching style and manner. It is important to correlate the evaluations with the degree of participation of the students in the evaluated activities, so the evaluation questionnaire includes quantitative questions regarding the number of participations in the teaching activities, but also qualitative criteria with open answers that allow the identification of the causes for which the students are absent from teaching activities.

Table 1. Questionnaire model used for evaluation

Criterion	Description	Type	Value range	Additional comments
Course	Select the assessed course	Categorial	List of courses	Necessary for course evaluation
I liked it	Briefly describe what you liked	Qualitative	Open answer	Useful for identifying the strengths of the course from the students' perspective
I didn't like it	Briefly describe what you didn't like	Qualitative	Open answer	It allows the identification of problems and of the areas that need improvement
I would have liked	Briefly describe what you would have liked	Qualitative	Open answer	Provides direct suggestions for improving the educational experience of the students
I attended the course	Select how many times you attended the course	Categorial	Never 2 or 3 times Half More than half Almost all All	Indicator of student participation in the course activity
I would have come more times to the course if		Qualitative	Open answer	It allows the identification of the main causes of students' non-participation in theoretical activities
I attended the seminar/laboratory	Select how many times you attended the seminar/laboratory	Categorial	Never 2 or 3 times Half More than half Almost all All	Indicator of student participation in applied activities
I would have come more times to the seminar/laboratory if		Qualitative	Open answer	It allows the identification of the main causes of students' non-participation in applied activities
Grade for course content	Rate the course content	Quantitative	1 - 10	Evaluation of the content taught in the course, from the point of view of their relevance and usefulness for students.
Grade for laboratory/seminar content	Rate the laboratory/seminar content	Quantitative	1 - 10	Evaluation of the content taught in the laboratory/seminar, focusing on practical and applied aspects.
Grade for the style and manner of teaching	Rate the teaching style and the teacher's involvement	Quantitative	1 - 10	Evaluating the teacher's teaching style, including clarity, engagement and interaction with students

3. Methodology

The proposed evaluation questionnaire model was applied to courses taught by a single teacher and 335 evaluations were collected for a number of 7 courses. All evaluations were carried out in Romanian. In order to be able to use more developed and much more tested lexicons than those available for the Romanian language, the evaluations were automatically translated from Romanian into English with the help of the Google Translate service and the Google Sheets application.

In order to analyze the textual content from the point of view of expressed sentiments, the text was first subjected to several preprocessing operations. For the preprocessing of the text, the stages present in the specialized literature were followed (Abdi et al., 2018; Peña-Torres, 2024). First, text transformation was applied. At this stage, all letters in the corpus were converted to lowercase, punctuation marks and special characters were removed, and abbreviations were converted to their extended versions. In addition, stop words and certain words considered insignificant for the analysis were removed in order to obtain the most relevant wordclouds. The tokenization of the texts at the word level and the normalization by applying the operations of stemming and lemmatization of the words obtained after the tokenization was performed. The UDPipe tool (Straka et al., 2016; Straka & Straková, 2017) was used for word stemming and lemmatization.

The VADER model was applied to analyze students' sentiments towards the evaluated courses. VADER is a popular sentiment analysis tool, particularly effective for social media text analysis (Hutto & Gilbert, 2014). It is a rule-based lexical model that can determine whether a text expresses a positive, negative, or neutral sentiment and that also provides a composite score that can take values between -1 (maximum negative) and 1 (maximum positive) to establish the general sentiment of an analyzed text. A composite score greater than or equal to 0.5 indicates an overall positive sentiment, a score between -0.5 and 0.5 indicates an overall neutral sentiment, and a composite score less than or equal to -0.5 indicates an overall negative sentiment.

4. Results

4.1 Analysis of the positive and negative aspects reported by students

By manually analyzing student responses, a teacher can find out in a direct and efficient way what students appreciate about his courses, what aspects are less appreciated and what aspects students would like to see improved. For a small amount of data, this manual feedback analysis is efficient. However, for a large volume of data, automatic analysis methods are needed.

For the automatic analysis of the positive and negative aspects reported by students, we used Wordcloud. Thus, from the initial data set we created three corpora consisting of two columns of the initial file, namely: Subject and "I liked", Subject and "I didn't like", Subject and "It would have been nice", respectively, in order to identify what the students appreciated, what they did not appreciate and what they would like to change in order to make the respective courses more useful and attractive for them. After obtaining the corpora, for each one, we removed the unanswered questions. We thus obtained the final corpora that were subjected to the preprocessing operations presented in the section dedicated to the description of the work methodology and, on the obtained results, we used the WordCloud as a visualization tool.

In order to obtain a WordCloud as suggestive as possible for the positive aspects, we applied to the corpus an additional list of stop words that did not bring additional information, their presence being obvious in a positive evaluation (I, like, liked, teacher, etc.) and we applied a rank 2 N-grams, the result being much more suggestive than in the case of a rank 1 N-grams. Thus, in figure 1, we can see that what the students appreciated the most in the evaluated courses was the teacher's teaching style (*"teaching style", "mode teaching", "way teaching", "teaching method"*), the way of explanation (*"explain well", "way explain", "way teach", "explain detail"*) and the fact that they learned many things or new things (*"learn many", "useful thing", "new thing", "learn new"*).

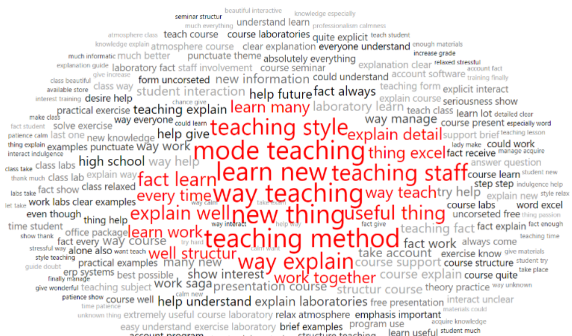

Figure 1. WordCloud for the criterion "*I liked it*"

For the analysis of the negative aspects, we applied a rank 2 N-grams and did not use any additional list of stop words. Although the students had to comment on the negative aspects of the courses taken, we see that there were quite a few answers that did not mention negative aspects (“*like everything*”, “*nothing object*”, “*nothing say*”, “*nothing complain*”). Among the negative aspects, objections related to the amount of activity and lack of time (“*large amount*”, “*short time*”, “*time allocated*”), the difficulty of paying attention in class (“*pay attention*”, “*class boring*”), laboratory requirements or objections related to the grid test (“*grid test*”, “*grid exam*”).

Figure 2. WordCloud for the criterion “*I didn’t like it*”

As for the answers regarding what the students would have liked related to the evaluated courses, there emerge from the obtained wordcloud certain wishes of the students related to the schedule of courses and laboratories (“*laboratory hour*”, “*laboratory Wednesday*”, “*class hour*”), certain preferences related to the accounting program studied or the programs they would have liked to study (“*account program*”), the emphasis laid on certain aspects, carrying out more practical exercises, more interactive classes, more detailed explanations to understand the subject better and to acquire more knowledge (“*acquire knowledge*”, “*learn lot*”, “*knowledge skills*”, “*understand better*”, “*better assimilate*”, “*little interactive*”,” *detailed explanation*”, “*put emphasis*”, “*practical work*”).

Figure 3. WordCloud for the criterion “*I would have liked*”

By using a questionnaire design such as that described in Table 1 if a large volume of data is collected, such analyses can be performed for each individual course, by year, by student attendance and by a combination of these criteria.

4.2 Analyzing student sentiments regarding the evaluated courses

Another open-answer qualitative evaluation automated analysis can be sentiment analysis. For this, we applied the VADER model.

Following the application of the VADER model, in order to evaluate the students’ reactions regarding the aspects they appreciated in the evaluated courses, we obtained the results represented in the Boxplot diagram in Figure 4. Interpreting the obtained diagram, we can determine the general tendency and the sentiment distribution for each and every course.

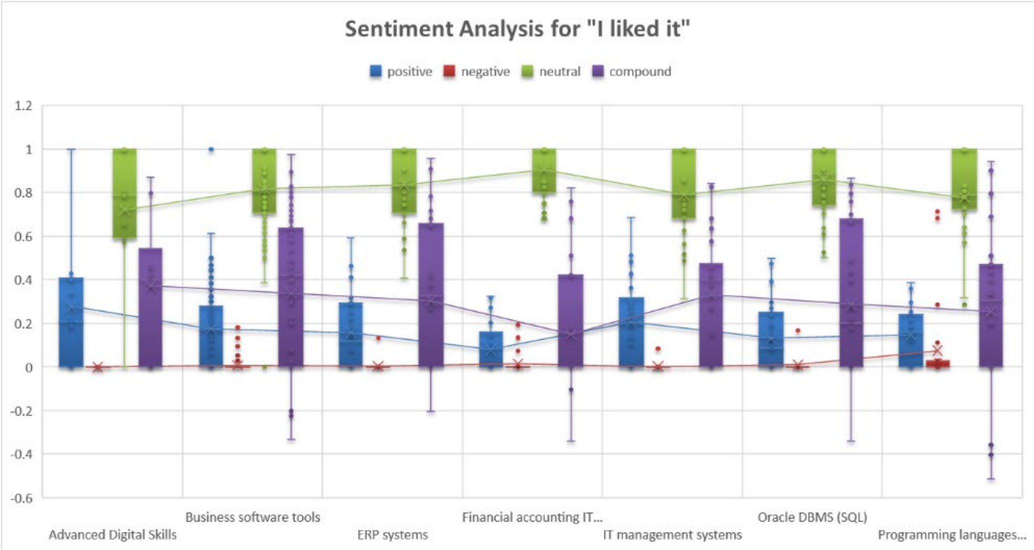

Figure 4. Sentiment analysis for the criterion "*I liked it*"

Table 2 shows the interpretations of the results obtained after applying the analysis to the answers related to what the students liked about each individual course.

Table 2. Interpretation of the Boxplot diagram for the criterion "*I liked it*"

Course	Interpretation
ADS	Clear prevalence of positive and neutral sentiments, with high composite scores indicating a moderate positive sentiment.
BST	A wider distribution of opinions is observed, with some students appreciating the course, while others had mixed or less favourable opinions, with an overall moderately positive sentiment.
ERP	Positive feelings are dominant, with high composite scores and very few negative feelings, indicating an overall positive perception.
FAITP	A wide range of responses is observed, including a significant number of negative sentiments, suggesting that while some students appreciated it, others were more critical, with the overall sentiment being less positive.
ITMS	It presents a balance between positive and neutral sentiments, but with fewer negative feelings, with the overall sentiment being moderately positive.
ODBMS	Predominantly neutral and composite scores are observed, with very few marked negative or positive reactions. The course was perceived as adequate, without standing out too much as being particularly attractive.
PLDB	It shows significant variability in sentiment, including negative and composite sentiments, indicating mixed opinions among students, with the overall sentiment being slightly positive.

***Abbreviations**: ADS – Advanced Digital Skills, BST – Business Software Tools, ERP – ERP systems, FAITP – Financial Accounting IT Products, ITMS – IT Management systems, ODBMS – Oracle DBMS (SQL), PLDB – Programming Languages for Databases (PLSQL)*

The diagram reflects a fairly broad spectrum of student perceptions regarding what they appreciated about the courses evaluated, which can help identify aspects that need improvement and maintain the positive aspects of the courses.

After analyzing the students' responses to the question regarding the aspects they did not appreciate in the evaluated courses, we obtained the results presented in the Boxplot diagram in Figure 5.

Figure 5. Sentiment analysis for the criterion "*I didn't like it*"

By interpreting the obtained diagram and the associated statistical values, we can determine the central tendency and distribution of students' sentiments regarding the analyzed aspect, for each course.

Table 3. Interpreting the Boxplot diagram for the "I didn't like it" criterion

Curs	Interpretation
ADS	Neutral feedback is generally observed, with composite values close to zero and predominantly neutral sentiments.
BST	It shows high variability in terms of negative sentiment, and the composite scores have a wide distribution, indicating that some students had very different reactions, with the overall sentiment being neutral to slightly negative.
ERP	It also shows a higher variation in negative sentiments and a wide distribution for the composite scores, which shows that the students' reactions were different, with the overall sentiment being neutral.
FAITP	It generally presents more neutral, but also negative scores, which suggests that students were not extremely dissatisfied, but not very enthusiastic either, the overall sentiment being neutral to slightly negative.
ITMS	More neutral scores are generally observed, but also negative ones, fact which suggests that students were not very dissatisfied, but not enthusiastic either, the overall sentiment being a neutral one.
ODBMS	Variability is observed in the composite scores suggesting that some students had more negative sentiments, while others were more positive or neutral.
PLDB	It shows a large variability in the composite scores, fact which suggests that some students had more negative sentiments, while others were more positive or neutral.

The results show that, while there are some courses that generate more negative reactions, most courses tend to have a mix of neutral and slightly positive feedback. The high variability of sentiments for some courses indicates a diversity in student perceptions, which could reflect both differences in teaching methods and differences in individual student expectations and experiences.

By applying the ANOVA (Analysis of Variance) test, we can determine whether there are statistically significant differences between students' sentiments about the courses evaluated. The F value indicates the magnitude of the differences, and the p value tests the null hypothesis, that there are no significant differences between the group means. A small p value, usually $p<0.05$, indicates that there are significant differences between the group means, which signifies that we can reject the null hypothesis. A p value>0.05, suggests that there are no significant differences between the group means, so we cannot reject the null hypothesis.

After applying the ANOVA test to the two analyses, we obtained the values in Table 4.

Table 4. ANOVA test results

	Sentiment analysis for „I liked it"				Sentiment analysis for „I didn't like it"			
	positive	negative	neutral	composite	positive	negative	neutral	composite
F-value	2.705	4.469	2.405	1.546	1.521	0.795	1.402	0.580
p-value	0.014	0.000	0.028	0.163	0.174	0.575	0.216	0.746

Regarding the analysis of what students appreciated about the courses evaluated, it is noteworthy that, although the differences between positive sentiments and neutral sentiments expressed by students for the courses evaluated are statistically significant ($p=0.014$, respectively $p=0.028$ – both less than 0.05), the magnitude of these differences is not very large ($F=2.705$, respectively $F=2.405$). This means that there are real variations between how students perceive the positive and neutral aspects of the courses, but these variations are of moderate magnitude. A greater variability ($F=4.469$), with strong statistical significance ($p=0.000$), is present in the negative sentiments expressed by students even in relation to what they appreciated in the evaluated courses, which suggests that students reacted very differently regarding the negative aspects and these reactions are highly significant, suggesting that the variation observed in the ANOVA is very important.

There is relative consistency in the composite scores, with lower variability ($F=1.546$), and these differences are not statistically significant ($p=0.163$). This suggests that the variability observed in the overall sentiments towards what students appreciated in the courses evaluated may be the result of normal fluctuations and does not reflect significant differences between courses.

In the analysis of the negative aspects identified by students in the evaluated courses, one may note that, for all polarities the F value is small or very small, which is statistically insignificant and suggests low variability (all p values are greater than 0.05). Based on these results, we can conclude that there are no statistically significant variations between the categories of sentiments (positive, negative, neutral, and composite) for the analyzed courses. This suggests that students' perceptions of what they did not like about the courses are relatively consistent between the courses, with no major differences that can be detected at a statistically significant level.

5. Limits and discussions

The results obtained show the large number of responses considered neutral and the very high values for the neutral scores. From the manual examination of the results obtained, we found that in the analysis of the criterion "I liked it", out of the 282 responses, 107 responses (37.94%) were evaluated as neutral with the maximum score of 1, in which case the composite score has the value 0. In the analysis of the criterion "I didn't like it", out of the total number of 181 responses, we found 71 (39.23%) responses evaluated as neutral. In addition to these, there are also responses that received very high values for the neutral score, generally values higher than 0.6, as can be seen from the two Boxplot diagrams.

There may be several possible reasons for the prevalence of these responses evaluated as neutral.

A first cause is the format of the questions in the questionnaire. The question statement contains the first part of the answer so that many students directly said what they liked or disliked without using the expressions "*I liked*", "*I didn't like*", "*I disliked*", etc., which have significant positive or negative polarities. Students gave answers, evaluated by the model as neutral, such as: "*the subject*" "*the teaching method*", "*everything*", "*too many requirements*", or "*too detailed explanations*" instead of "*I liked the subject*", "*I liked the teaching method*", "*I liked everything*", "*I didn't like that there were too many requirements*" or "*I disliked that there were too detailed explanations*", which have obviously positive or negative polarities.

Another reason could be the generalized and formal feedback of students who tend to use formal or neutral language to describe their experiences. Comments such as "*the course was ok*" or "*it was good*" do not necessarily express strong emotions, positive or negative. Added to this may be the hesitation of students to criticize or praise excessively in order not to seem too critical or too laudatory, which leads to the use of moderate or neutral formulations. Students may also use more restrained language in such feedback. For example, they may avoid using words with extreme connotations (very good, excellent, terrible) and, instead, prefer terms such as "*acceptable*", "*adequate*", "*satisfactory*" or "*ok*", which lead to neutral labels.

The VADER model is a model optimized for short, informal language, such as tweets and online reviews. (Saha et al., 2023) As we have seen, however, the language used by students in such feedback can be more ambiguous and less emotional, making it difficult to detect clear sentiments. In such cases, VADER may mislabel comments as neutral even if they contain emotional subtleties.

The VADER model may also have low sensitivity to context. It does not always take into account the specific context in which sentiments are expressed. (Dhanalakshmi et al., 2023) In a response in which students express complex sentiments, the model may label the response as neutral even when there are emotional subtexts. The VADER model, while effective in many contexts, has a tendency to assign neutral values when it cannot clearly detect a polarity. (Dhanalakshmi et al., 2023) This bias can occur when the text is ambiguous or when there are no highly emotional words. Thus, the model may assign a neutral polarity when it cannot clearly establish a positive or negative sentiment.

Following the analysis, we can say that the VADER model can be used for a quick and minimal effort analysis of students' sentiments towards the evaluated courses, but additional actions are needed for more accurate results.

One of the directions for improving the analysis results would be the integration of a hybrid model that combines VADER with more advanced models, such as BERT or RoBERTa, which are able to better capture the context and subtext of the expressed emotions. Models based on deep learning, such as those mentioned, can provide a more accurate interpretation of formal text and subtle sentiments, improving the detection of mixed or moderately expressed sentiments. Comparative research (Saha et al., 2023) has shown that VADER can be complemented with models such as BERT to improve the accuracy in analyzing more complex sentiments.

Since VADER is based on a predefined lexicon, which is not always optimal for the language used in educational assessments, another direction to improve the results would be to develop a specific lexicon for the language used in the educational field, adapted to the common words and phrases found in student feedback. Customizing the lexicon can help to capture sentiment more accurately in this specific field.

Manual assessment of data can bring a higher level of validity to sentiment analysis, especially in detecting subtleties that an automatic model, such as VADER, misses. Therefore, another direction to improve the results of such an analysis could be to develop a semi-automatic model, in which automatic sentiment analysis is combined with manual assessments for part of the data. This would allow for checking the correctness and adjusting the automatic model to calibrate the automatic results and improve the algorithms on a long-term basis.

6. Conclusions

Adopting an integrated mixed model for assessing student satisfaction is supported by recent research and offers a promising way to overcome the limitations of traditional assessment methods used in education. By combining quantitative data with detailed qualitative analyses, such a model can provide a more holistic and nuanced understanding of student experience, thereby facilitating continuous improvement in the quality of the educational process.

The proposed mixed model, which contains quantitative and general qualitative criteria, by means of a manual analysis performed by each evaluated teacher, can provide valuable information regarding the general positive and negative aspects of his activity as well as what the students would like to see improved. On the other hand, integrating such a model into an automatic evaluation system of students' sentiments towards the courses taken, requires significant additional efforts as we have shown in the Limits and discussions section.

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