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Application of opinion mining techniques in the study of the perception of remote attendance in higher education institutions

Aplicación de técnicas de minería de opinión en el estudio de la percepción sobre la presencialidad remota en instituciones de educación superior

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Abstract

Introduction: the COVID-19 pandemic significantly impacted the education sector, prompting universities to adapt to remote attendance. Understanding students' perceptions of these adaptations is crucial for enhancing academic processes and preparing for hybrid education models. **Objective:** this study aims to analyze students' perceptions of remote attendance at the University of Cartagena using opinion mining techniques. **Methodology:** the research follows a descriptive and quantitative approach, employing opinion mining as an analysis tool. Data were collected through a perception survey with five open-ended questions applied to a sample of 46 Systems Engineering students. Responses were preprocessed and analyzed using natural language processing (NLP) techniques and sentiment analysis with the Paralleldots Python library. **Results:** the polarity analysis revealed a positive-to-negative ratio of 1.25, suggesting a generally favorable perception of remote attendance. However, concerns

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emerged regarding pedagogical adaptation and student engagement. **Conclusions:** the study demonstrates the relevance of opinion mining in educational research, providing quantitative insights from qualitative data. These findings can inform institutional decision-making and extend to other domains such as marketing and user experience analysis.

Keywords: affective computing, COVID-19, opinion mining, remote presence, sentiment analysis.

Resumen

Introducción: la pandemia de COVID-19 impactó significativamente la educación, llevando a las universidades a adoptar la presencialidad remota. Evaluar la percepción estudiantil sobre este modelo es clave para mejorar los procesos académicos y preparar la transición a la educación híbrida. **Objetivo:** este estudio busca analizar la percepción de los estudiantes sobre la presencialidad remota en la Universidad de Cartagena mediante técnicas de minería de opinión. **Metodología:** la investigación tiene un enfoque cuantitativo y descriptivo, utilizando minería de opinión como herramienta de análisis. Se recopiló información mediante una encuesta de percepción con cinco preguntas abiertas, aplicada a una muestra de 46 estudiantes de Ingeniería de Sistemas. Las respuestas fueron preprocesadas y analizadas con técnicas de procesamiento de lenguaje natural (PLN) y análisis de sentimientos usando la librería Paralleldots en Python. **Resultados:** el análisis de polaridad mostró una relación de 1.25 entre la polaridad positiva y negativa, lo que indica una percepción mayormente favorable de la presencialidad remota. Sin embargo, se identificaron desafíos en la adaptación pedagógica y el compromiso estudiantil. **Conclusiones:** el estudio resalta la pertinencia de la minería de opinión en el análisis educativo, permitiendo obtener métricas cuantitativas a partir de datos cualitativos. Estos resultados pueden apoyar la toma de decisiones institucionales y extenderse a otros ámbitos como el marketing y la experiencia del usuario.

Palabras clave: análisis de sentimientos, computación afectiva, COVID-19, minería de opinión, presencialidad remota.

Introduction

The COVID-19 pandemic has wielded a substantial impact on the economy, industry, education, and health. Consequently, various activities carried out within businesses and educational institutions had to adapt to virtual modalities, supported by Information and Communication Technologies (ICT) (Chanchí y Hernández-Londoño, 2020; Gautam et al., 2022; Liu et al., 2022; Seow et al., 2022). In the context of academic processes within universities, a methodology known as remote attendance, was embraced. This compelled university professors to adjust their teaching-learning methods and assessment strategies to the dynamics of virtuality. Simultaneously, students were required to enhance their skills in autonomous work (García et al., 2021; Guenther et al., 2022; Havik y Ingul, 2022; Lichand et al., 2022; Montes-Rodríguez et al., 2020; Oloyede et al., 2022). In this regard, it has been crucial for institutions of higher education to assess students' perceptions, aiming not only to enhance their academic processes but also to prepare for the eventual transition to a hybrid in-person-remote approach post-pandemic.

In this context, Sentiment Analysis and Affective Computing have emerged as key tools to assess user perception from qualitative data. Affective Computing (Picard, 2000) studies the interaction between humans and machines based on emotions, while Sentiment Analysis (Pang y Lee, 2008) allows the extraction of quantitative indicators from subjective texts using natural language processing (NLP) techniques. Although one of the most widespread ways to evaluate the perception of a user or customer with respect to a product, service or experience are the so-called perception surveys, one of the existing challenges is the analysis of the qualitative or subjective information contained in each opinion, in order to obtain quantitative indicators that allow estimating the real perception of the customer or end user (Alamoodi et al., 2021; Kirtibas-Singh y Renuga-Devi, 2021; Singh et al., 2022). Under these circumstances, one emerging area within computer science is affective computing, which, through the use of computational techniques based on natural language processing, such as sentiment analysis or opinion mining, enables the extraction of emotional value or polarity (positive, negative, or neutral) associated with a specific opinion (Birjali et al., 2021; Li et al., 2022; Liu et al., 2021; Saura et al., 2018; Zhao y Yu, 2021; Zhou et al., 2021). These methodologies have been widely used in areas such as marketing, healthcare and social media, but their application in education is still a developing field.

Different works have been carried out around the topic of perception analysis in different application contexts, by using sentiment analysis techniques. For example, Alamoodi et al. (2021) analyzed student opinions in educational forums, while Singh et al. (2022) applied opinion mining to teacher satisfaction surveys. However, there is a gap in the literature regarding the application of these techniques to remote face-to-face perception surveys. This study seeks to fill that gap by offering an opinion mining approach to characterize the perception of Systems Engineering students at the University of Cartagena on the first semester of remote attendance. Thus, in Ikoro et al. (2018) develop a sentiment analysis study on the comments made on the social network Twitter regarding the energy service in the United Kingdom, making use of a specialized lexicon specific to the knowledge domain considered. In Sathya et al. (2019) develop a model based on natural language processing and sentiment analysis for monitoring public opinion on trending topics on the social network Twitter, in order to determine the emotionality and/or polarity expressed in the different opinions corresponding to each trend. In Koneru et al. (2018) conducted a perception study based on sentiment analysis on the opinions expressed by Twitter users regarding the five most recognized cloud service providers (Amazon, Microsoft Azure, Sales force, IBM Cloud and Google Cloud) in order to support decision making in the acquisition of new services by potential customers. Similarly, in Al-Hajjar y Syed (2015) developed a sentiment analysis study in order to identify the perception on the opinions made by Twitter users regarding 10 technology brands (Apple, Google, Microsoft, Samsung, GE, IBM, Intel, Facebook, Oracle and HP). In Wariishi et al. (2015) conducted a perception study supported by sentiment analysis on the opinions expressed in reviews associated with wines and their aromas, with the purpose of supporting decision making by companies in terms of marketing and at the level of products that customers can purchase. In Seetharamulu et al. (2020) proposed a deep learning-based model for conducting sentiment analysis studies on product and service reviews in the context of marketing, which obtained higher accuracy with respect to other techniques identified in the state of the art. In Rane y Kumar (2018) conducted a sentiment analysis study to identify the perception contained in Twitter users' opinions regarding the services offered by six U.S. airlines, in order to propitiate decision making and feedback the information obtained by the airlines through their perception questionnaires. In Park (2020) developed a sentiment analysis study on the comments made by customers of 26 major cosmetic brands in the world, in order to obtain the relative satisfaction of customers with the brands and the main causes of comments with positive or negative polarity. In Saura et al. (2018) a sentiment and/or polarity analysis study was developed on the opinions made by Twitter users regarding the offers published through the hashtag #BlackFriday during November 24, 2017, identifying the fluctuation of sentiments throughout the event. In Gil-Vera (2018) a text and opinion mining study was conducted to identify the perception of the beneficiaries of the organization "TECHO" in Latin America, through polarity analysis on a total of 1000 comments made on the social network Twitter.

The previously presented works illustrate the widespread adoption of affective computing, particularly sentiment analysis and/or opinion mining techniques, for identifying customer perceptions of various products and services within the marketing context. This is achieved through the processing and analysis of comments made across various digital platforms, predominantly social media. In this regard, it is evident that, despite the advantages offered by sentiment analysis techniques in obtaining quantitative information from qualitative data, their dissemination has primarily occurred in the field of marketing. However, the benefits of these techniques can potentially be extrapolated to the educational context for discerning the perceptions of students and educators during various academic activities.

The present article differs from previous studies by applying a systematic sentiment analysis approach to qualitative surveys in a post-pandemic educational context. The main contribution lies in demonstrating the feasibility of these techniques to obtain quantitative metrics from open-ended responses in perception surveys. In addition, polarity trends in student opinions are explored, providing relevant information for decision making in hybrid educational models.

In this article, we propose, as a contribution, the use of sentiment analysis as a mechanism to aid in identifying students' perceptions within the educational context of remote attendance. The developed study aims to serve as a reference for decision-making by the leadership of the University of Cartagena regarding the strengthening of virtual program offerings post-pandemic. Similarly, this study seeks to contribute to the dissemination of affective computing methods as tools for obtaining quantitative indicators related to the development of various academic activities by students and university professors.

Method

This study follows quantitative, descriptive, and cross-sectional research design, employing opinion mining techniques to analyze students' perceptions of remote attendance. The descriptive approach allows for characterizing and interpreting students' sentiments without manipulating variables, while the cross-sectional nature ensures that data collection captures perceptions at a specific moment in time, namely, the conclusion of the first semester of remote attendance.

The primary contribution of this article lies in the development of a study based on affective computing, specifically focusing on sentiment analysis to characterize the perceptions of students in the Systems Engineering program at the University of Cartagena regarding the first semester of remote attendance due to the COVID-19-induced lockdown. To achieve this, a survey with qualitative questions was conducted among a sample of 46 students from the Systems Engineering program after the conclusion of the first semester of remote attendance. The polarity of the responses obtained by the students was analyzed using the sentiment analysis library, Paralleldots, in the Python language, following the appropriate adaptation and cleaning of the responses (removing line breaks, addressing missing characters, and correcting spelling errors). The survey questions were designed to inquire about aspects such as the university's management of academic processes, the conduct of classes and evaluations, how students organized their time for completing activities, and the impact on the quality of education resulting from remote attendance.

For data collection, an open-ended perception survey was chosen as the primary research instrument (see Table 1). This choice was based on its ability to capture subjective opinions while allowing computational sentiment analysis to generate quantitative insights. Unlike multiple-choice surveys, which restrict responses to predefined categories, open-ended questions provide a richer source of qualitative data, enabling a more accurate sentiment analysis. Other alternatives, such as structured interviews or focus groups, were not considered due to time constraints and the need for a standardized and scalable data collection method.

The remainder of the article is organized as follows: This section describes the different methodological phases considered for the development of this research. In the next section (results), the results obtained in this perception study are presented, including the analysis of polarity distribution in responses to survey questions, as well as the analysis of dominant polarities. Finally, in section discussion and conclusions, conclusions, the discussion of results, and future work derived from this research are presented.

For the development of the research presented in this article, four methodological phases were defined, namely: design and application of the instrument, cleaning and adaptation of responses, analysis of the polarity of responses, and generation of study conclusions (see Figure 1).

Figure 1
Methodology considered

In phase 1 of the methodology, the design of the perception survey was conducted. The survey consists of a total of 5 open-ended questions and was administered to a sample of 46 students from the Systems Engineering program at the University of Cartagena who enrolled in an elective course during the first semester of remote attendance. This includes students from the seventh, eighth, ninth, and tenth semesters.

The sample was selected using a non-probabilistic convenience sampling approach (Arbeit y Horn, 2017; Bornstein et al., 2013), ensuring that participants had direct experience with remote education. Demographically, the participants were aged between 20 and 25 years, with both male and female students included, reflecting the general distribution of students in the program.

For the calculation of the sample size, equation 1 was employed (Aguilar-Barojas, 2005; Rositas-Martínez, 2014; Vargas-Biezus, 2014), which enabled the determination of the minimum number of students to be surveyed (n) based on the population of students in the final semesters of the program or those who enrolled in an elective (N).

$$n = \frac{N * Z_{\alpha}^{2} * p * q}{e^{2} * (N-1) + Z_{\alpha}^{2} * p * q} \qquad (1)$$

In Equation 1, *N* corresponds to the population size, *Za* represents the Chi-square table value associated with the confidence level. Similarly, the variables *p* and *q* are associated with the probability in favor and against, while e represents the associated error. Thus, the values substituted into the equation are: *N=120*, *Za = 1.96* (value corresponding to a 95% confidence level), *p=0.95* (probability in favor), *q=0.05* (probability against), *e=0.05* (expected error). As a result of substituting these values into the equation, the minimum sample size is calculated to be 45.6 students.

The survey questions addressed 5 aspects related to the development of academic activities during the pandemic, including how the University managed different academic processes during remote attendance, the manner in which classes were conducted during remote attendance, the approach to assessment activities in various courses, how students organized their time for different academic activities during remote attendance, and finally, the opinion on whether the quality of education was affected during the activities in confinement. Table 1 presents the 5 questions considered in the study.

Table 1
Questions defined in the opinion mining study

	Question
1	What is your opinion about the way in which the University managed the different academic processes in remote attendance?
2	"What are your thoughts on the way classes were conducted through remote attendance at the University?
3	What is your opinion regarding the manner in which assessment activities were conducted in the various courses?
4	In what way have you organized and carried out your academic activities to effectively fulfill the objectives of the different courses?
5	Do you believe that remote attendance impacted the quality of university education? Justify your response.

In Phase 2 of the methodology, the cleaning and adaptation of the responses provided by the 46 students who participated in the survey were carried out. This involved removing line breaks at the end of each response, correcting the use of accents, and replacing incorrect characters. These actions aimed to enhance the accuracy of the polarity classification model used by the Paralleldots library. In Phase 3 of the methodology, polarity analysis was applied to the responses of the 5 questions using the opinion mining library Paralleldots, along with the data analysis libraries Pandas and NumPy in Python. The objective was to determine both the polarity distribution and the dominant polarity for each question, aiming to obtain a more objective perception regarding the development of activities during the first semester of remote attendance at the University of Cartagena. Finally, in Phase 4 of the methodology, the results obtained in Phase 3 are consolidated to derive conclusions from the perception study conducted.

Regarding ethical considerations, participation in the study was voluntary, and all students provided informed consent before answering the survey. The survey was designed to ensure anonymity, with no personally identifiable information collected. The study adhered to ethical research standards for working with human participants, ensuring that the data were used solely for academic purposes.

Results

In this section, the results and discussion of the current research are presented, incorporating the analysis of polarity distribution and dominant polarity for each of the responses to the 5 questions considered in the perception survey (see Table 1). The opinion mining study presented in this article was conducted on the Google Colab cloud computing platform using the sentiment analysis library and the data analysis and processing libraries mentioned in the methodology section. Regarding the polarity analysis of the first question, which inquired about how the University managed various academic processes during remote attendance, the polarity distributions obtained are illustrated in Figure 2.

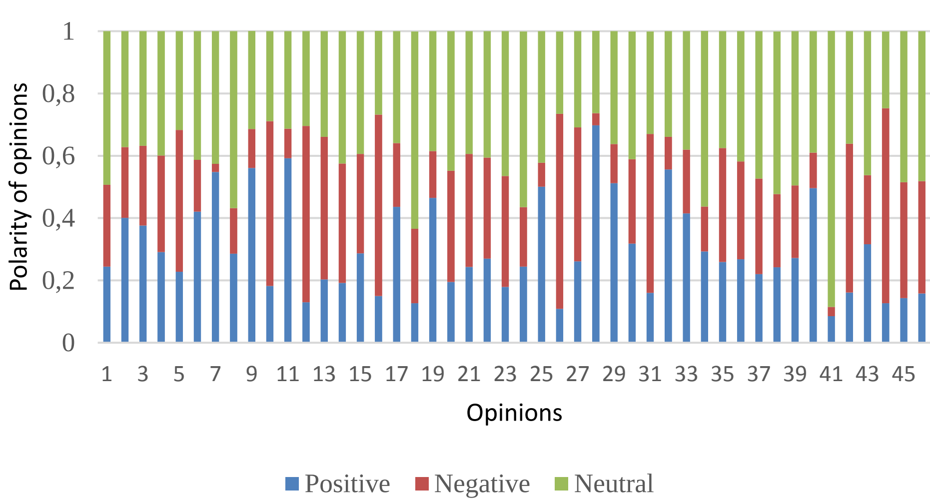

Figure 2
Analysis of polarity distribution in question 1

Based on the findings presented in Figure 2, it can be observed that the polarity exhibiting the highest distribution among the 46 opinions is neutral, followed by positive and negative polarities. In this regard, the total average of neutral polarity is 0.411, while the average for positive polarity is 0.3, and the average for negative polarity is 0.289, indicating a ratio between positive and negative polarities of 1.041. Furthermore, by tallying the dominant or prevailing polarities in each opinion, the pie chart in Figure 3 can be generated.

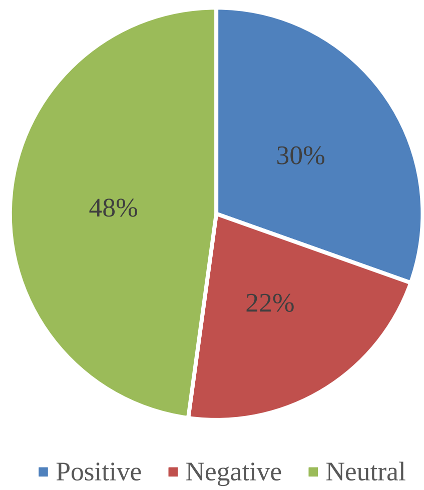

Figure 3
Distribution of dominant polarities in Question 1

According to Figure 3, it is possible to observe that neutral polarity is dominant in 48% of opinions, while positive polarity is dominant in 30%, and negative polarity is dominant in 22%. In this context, although students acknowledge that the transition from in-person to remote attendance was not flawless, they highlight the measures taken by the university in formulating agreements that provided guidelines regarding the flexibility of assessment activities and the possible tools to be used in classes (Google Suite: Google Meet, Google Classroom, etc.). Similarly, students highlighted as an aspect to improve the training of teachers in the adaptation of the pedagogical methodology to the dynamics of virtuality, since in some courses the methodology with which the courses were developed was the same as the one used in face-to-face education, making the appropriation of the different topics difficult.

On the other hand, for the analysis of polarity in the second question, which inquired about how classes were conducted during remote attendance at the University, the polarity distributions presented in Figure 4 were obtained.

According to the findings presented in Figure 4, it is possible to observe that the polarity with the highest participation or distribution in the 46 opinions is neutral, followed by positive polarity and negative polarity. Thus, the total average of neutral polarity is 0.423, while the average for positive polarity is 0.347, and the average for negative polarity is 0.230, indicating a ratio between positive and negative polarities of 1.505. On the other hand, considering the count of the dominant polarities in the 46 opinions, it is possible to obtain the graph presented in Figure 5.

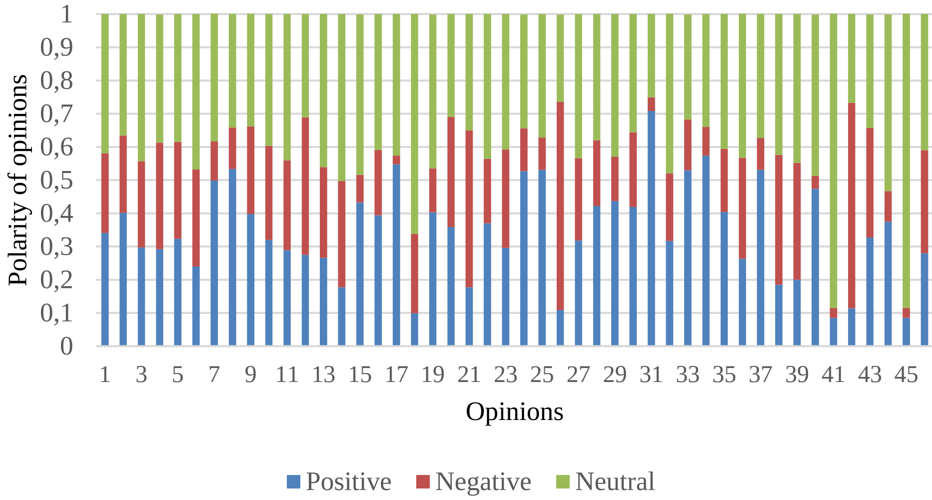

Figure 4
Analysis of polarity distribution in question 2

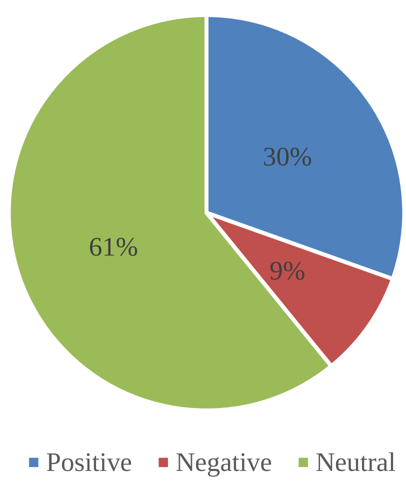

Figure 5
Distribution of dominant polarities in question 2

According to Figure 5, it is possible to observe that neutral polarity is dominant in 61% of opinions, while positive polarity is dominant in 30%, and negative polarity is dominant in 9%. In terms of positive comments, students highlight the flexibility of assessment activities in the courses, the ability to access class recordings at any time, and the efficiency in terms of the device or location from which they could connect to classes. Similarly, in terms of aspects to be improved, the students mention that in some courses the classes were developed in a similar way to face-to-face education, being necessary to adapt the methodology to the dynamics of virtuality, promoting participation and dynamism. In this sense, they emphasize that the University should not only encourage more training of university professors in the use of technological tools, but also in the appropriate methodologies to guide the classes during remote attendance.

For the polarity analysis of the third question, inquiring about how assessment activities were conducted in different courses during remote attendance, the polarity distributions presented in Figure 6 were obtained.

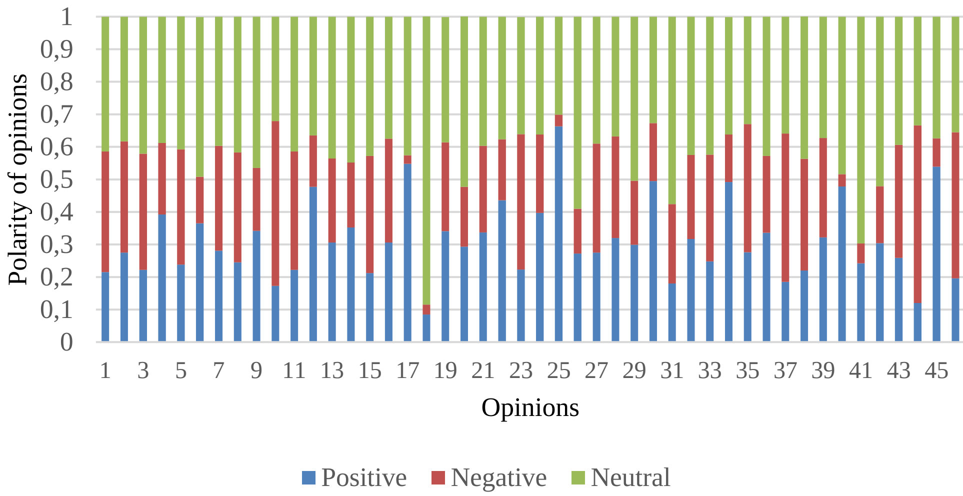

Figure 6
Analysis of polarity distribution in question 3

According to the findings presented in Figure 6, it is possible to observe that the polarity with the highest participation or distribution in the 46 opinions is neutral, followed by positive polarity and negative polarity. Thus, the total average of neutral polarity in the 46 opinions is 0.427, while the average for positive polarity is 0.311, and the average for negative polarity is 0.262, indicating a ratio between positive and negative polarities of 1.187. On the other hand, considering the count of the polarities that are greater or dominant in the 46 opinions, it is possible to obtain the graph presented in Figure 7.

Based on Figure 7, it is possible to observe that neutral polarity is predominant in 67% of the opinions, while positive polarity is dominant in 20% of the opinions, and negative polarity is dominant in 13% of the opinions. In this regard, students positively emphasized the fact that the University provided flexibility in the development of assessment activities, allowing professors the freedom to conduct the number of activities they deemed appropriate during the semester, without being limited to the 3 traditional or partial assessments used in face-to-face education. In this context, students highlighted the flexibility in the deadlines for assessment activities in different courses. On the other hand, students highlighted that, as the assessment activities were different from traditional exams, they were able to develop investigative skills in various topics and strengthen their writing and information synthesis skills. Despite the advantages mentioned earlier regarding flexibility, students mentioned that not all professors were flexible in assessment activities and continued to conduct traditional partial exams. Similarly, due to the flexibility in the submission of assignments, some professors scheduled assessment activities at the end of the semester, increasing the number of assignments and academic workload.

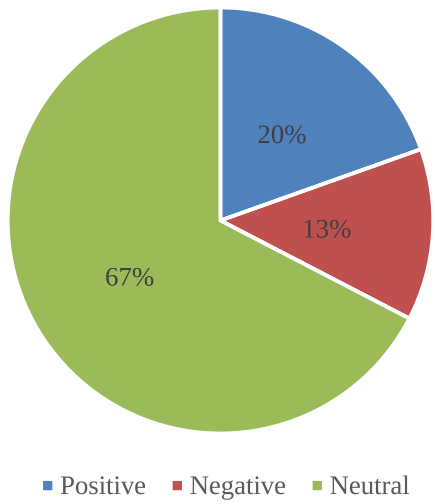

Figure 7
Distribution of dominant polarities in question 3

On the other hand, regarding the analysis of polarity for the fourth question, which inquired about how students have organized and carried out academic activities to fulfill the objectives of different courses, the polarity distributions presented in Figure 8 were obtained.

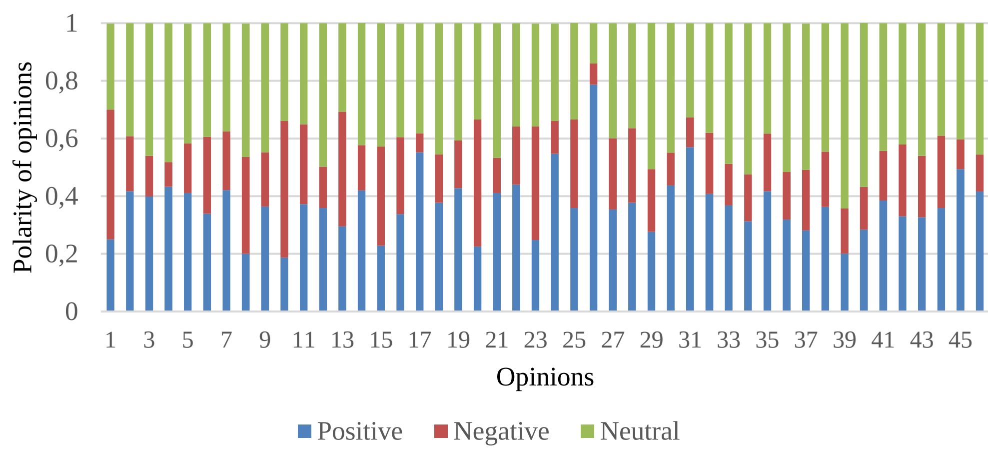

Figure 8
Analysis of polarity distribution in question 4

In accordance with the findings presented in Figure 8, it can be observed that the polarity with the highest participation in the opinions is neutral, followed by positive and negative polarities. Thus, the overall average of neutral polarity in the 46 opinions is 0.416, while the average for positive polarity is 0.371, and the average for negative polarity is

0.213, resulting in a ratio between positive and negative polarities of 1.745. On the other hand, by considering the count of dominant or major polarities in the 46 opinions, the graph presented in Figure 9 can be obtained.

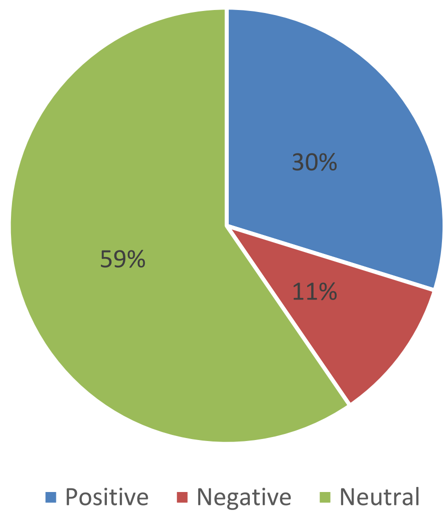

Figure 9
Distribution of dominant polarities in question 4

In Figure 9, it is possible to observe that neutral polarity is dominant in 59% of the opinions, while positive polarity is dominant in 30% of the opinions, and negative polarity is dominant in 11% of the opinions. In this regard, students highlighted that during remote attendance, they developed their ability to better organize their time, managing activities assigned by priorities, even making use of time management methodologies like Kanban. Likewise, they highlight that remote attendance allowed them to make the most of the time they previously spent on transportation to the University by advancing assignments and reinforcing what they learned through online courses and videos on Youtube. On the other hand, as an area for improvement, students mention that academic flexibility led to an increase in the number of assignments, especially towards the end of the semester.

Continuing with the analysis, concerning the polarities associated with question five, which inquired whether remote attendance affected the quality of university education, the polarity distributions presented in Figure 10 were obtained.

According to the findings presented in Figure 10, it is possible to observe that the polarity with a higher presence in the opinions is neutral, followed by negative and positive polarities. In this regard, the total average of neutral polarity in the 46 opinions is 0.398, while the average for negative polarity is 0.306, and the average for positive polarity is 0.295, resulting in a ratio between positive and negative polarities of 0.67. This indicates that, of the five questions, question 5 is the only one in which negative polarity surpasses positive polarity. On the other hand, considering the count of dominant or major polarities in the 46 opinions, the graph presented in Figure 11 can be obtained.

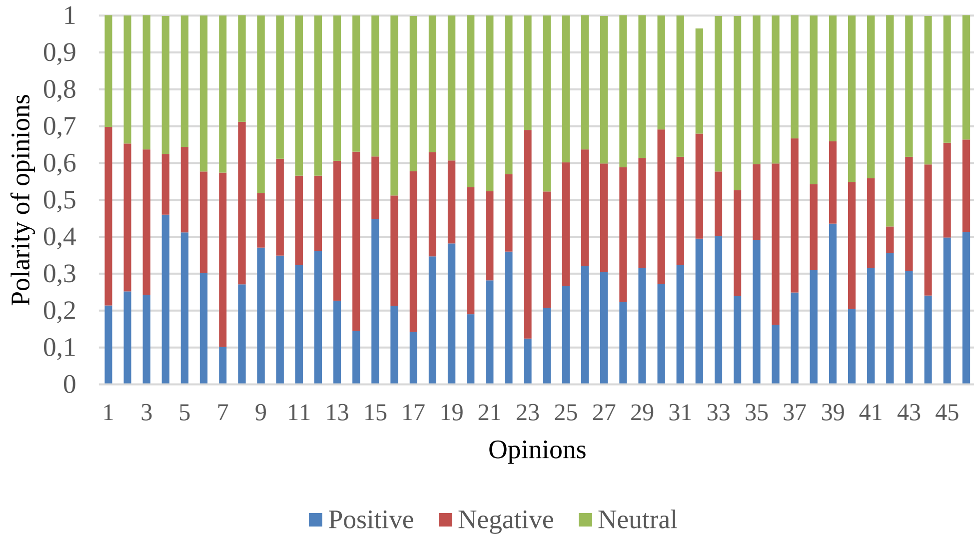

Figure 10
Analysis of polarity distribution in question 5

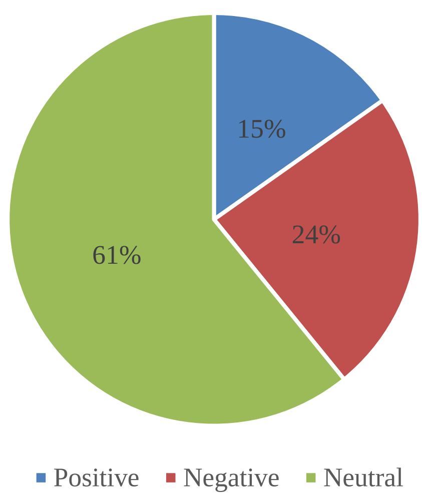

Figure 11
Distribution of dominant polarities in question 5

In Figure 11, it can be observed that neutral polarity is dominant in 61% of the opinions, while negative polarity is dominant in 24% of the opinions, and positive polarity is dominant in 15% of the opinions. In this regard, students expressed that the quality of education was affected in the sense that competencies associated with laboratory practices were not adequately developed. In the same way, students mentioned that the difficulty to adapt to the dynamics of virtuality on the part of professors and students meant that classes did not have the same or similar interaction as face-to-face classes, causing the motivation for the classes to diminish. In the same vein, the students consider that the 3 exams or partial exams that are normally developed in face-to-face classes contribute to cultivate the demand in the development of the objectives of the course, with respect to the flexibility with which the remote face-to-face classes were managed. As positive aspects, the students highlighted that remote attendance contributed to promote self-learning and organization in the development of academic activities.

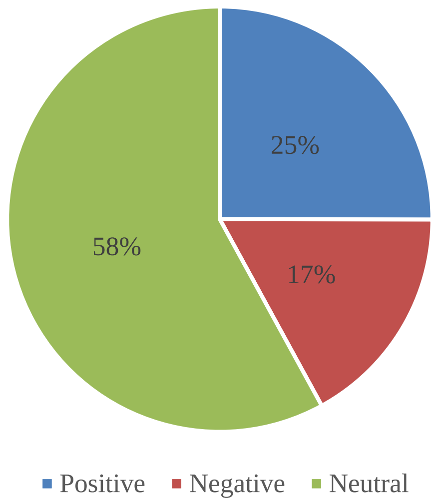

Figure 12
Average distribution of dominant polarities

To conclude, if an average is taken of the polarity obtained for students' responses to the 5 questions, it is found that neutral polarity had an average value of 0.415, followed by positive polarity with a value of 0.325, and negative polarity with a value of 0.260. Thus, the ratio between positive polarity and negative polarity was 1.25, which can be explained by the fact that in 4 out of the 5 questions, positive polarity was higher than negative polarity, while negative polarity was higher than positive in question 5. Similarly, if the average percentages of dominant polarities in the 5 questions is calculated, it is found that on average, in 58.215% of opinions, the dominant polarity is neutral, while in 25.14% of opinions, the dominant polarity is positive, and in 17.079% of opinions, the dominant polarity is negative (see Figure 12).

In general, there is a positive perception regarding the aspects addressed in the perception survey and related to the development of academic activities during the pandemic. This is evidenced by obtaining a ratio of 1.25 between the average positive and negative polarity of the total responses to the 5 questions. In this regard, in the first 4 questions, a ratio greater than 1 was obtained between positive and negative polarities, while in the fifth question regarding how the quality of higher education has been affected, a ratio less than one was obtained. Thus, regarding this aspect, students believe that the lack of training in both the use of technologies and shortcomings in adapting pedagogical practices to the dynamics of virtuality affected the quality of classes. Similarly, students mentioned that, although the flexibility of classes was a positive aspect, the absence of partial exams led to a decrease in the rigor of the courses.

Discussion and conclusions

As part of the discussion, it is important to mention that the current study, unlike sentiment mining-based studies presented in (Cai et al., 2020; Gil-Vera, 2018; Ikoro et al., 2018; Saura et al., 2018), is not applied to datasets obtained from social networks such as Twitter. On the contrary, sentiment analysis techniques apply to a perception survey, utilizing pre-trained sentiment classification models. This approach opens the possibility of extrapolating the present approach to other perception analysis studies in contexts other than education, such as marketing, enriching the methods of perception survey analysis. Similarly, in contrast to studies presented in (Chanchí y Hernández-Londoño, 2020; Monterrosa-Castro et al., 2023), where perception analyses in the educational context during the pandemic are conducted through the use of descriptive statistical methods on quantitative survey questions, the present study outlines a novel approach based on opinion mining. This approach enables the derivation of quantitative perception values from the analysis of qualitative information, such as opinions. Thus, this innovative approach enhances researchers' tools by complementing the results of a perception survey. It allows for the juxtaposition of the analysis conducted on quantitative questions with the analysis obtained from qualitative questions, utilizing computational opinion mining techniques.

The application of sentiment analysis in education has been explored in different contexts. For instance, Alamoodi et al. (2021) demonstrated the effectiveness of computational sentiment analysis in evaluating students' emotional responses to online learning, while Singh et al. (2022) applied similar techniques to assess faculty satisfaction. The present study expands on these findings by demonstrating that sentiment analysis can provide insights into student perceptions of remote attendance, a dimension that remains underexplored in literature. Moreover, unlike previous studies that have primarily relied on structured surveys with predefined sentiment scales, this study leverages opinion mining techniques for the analysis of open-ended questions, allowing for the extraction of quantitative insights from qualitative data without requiring the individuals under study to conform to predefined sentiment scale responses.

In this work, the contribution proposed was the development of a perception study on the academic activities of Systems Engineering students during the COVID-19 pandemic, utilizing affective computing techniques, specifically opinion mining. Previous studies have used perception analysis in education during the pandemic (Chanchí-Golondrino et al., 2022; Monterrosa-Castro et al., 2023), but they mainly relied on descriptive statistical methods. This research expands on their approach by applying sentiment analysis techniques to qualitative survey responses, allowing for a deeper understanding of students' perceptions. The study aimed to analyze the opinions of a sample of students from the University of Cartagena regarding various aspects of remote attendance. These aspects include the measures taken by the University to manage different academic processes during the lockdown, the manner in which classes were conducted during remote attendance, the execution of assessment activities in different courses, how students organized their time for economic activities, and how remote attendance impacted the quality of university education. By leveraging sentiment analysis methodologies (Alamoodi et al., 2021; Saura et al., 2018), this study demonstrates how computational techniques can provide structured insights into subjective opinions, making them valuable tools for decision-making in education. This study seeks to serve as a reference for disseminating sentiment analysis in the educational context, aiming to identify the perceptions of students across different educational levels within teaching and learning processes.

In this work, the contribution proposed was the development of a perception study on the academic activities of Systems Engineering students during the COVID-19 pandemic, utilizing affective computing techniques, specifically opinion mining. The study aimed to analyze the opinions of a sample of students from the University of Cartagena regarding various aspects of remote attendance. These aspects include the measures taken by the University to manage different academic processes during the lockdown, the manner in which classes were conducted during remote attendance, the execution of assessment activities in different courses, how students organized their time for economic activities, and how remote attendance impacted the quality of university education. This study seeks to serve as a reference for disseminating sentiment analysis in the educational context, aiming to identify the perceptions of students across different educational levels within teaching and learning processes.

From the challenge of analyzing qualitative data or information, such as people's opinions in different digital media or perception surveys, sentiment analysis techniques emerge as a useful alternative to obtain quantitative or objective indicators from opinions, which is represented in the polarity value of an opinion (positive, negative, and neutral). The advantages of these techniques have been highlighted in various domains, including customer experience analysis (Rane y Kumar, 2018) and public health perception studies (Liu et al., 2021). The findings of this study suggest that educational institutions could leverage sentiment analysis to continuously monitor students' perceptions and adjust academic policies accordingly. In this sense, and taking into account the existence of free and proprietary tools and/or libraries that allow obtaining polarity from the text associated with an opinion, there is a great potential for the application of these techniques in contexts such as industry, marketing, tourism and education, in order to obtain the perception of users and/or potential customers of different products and services.

In this paper, the advantages provided by the Python Paralleldots and Pandas libraries were used to determine and process the polarities of an opinion. In this sense, the Paralleldots library allows to obtain the distribution of polarities or level of each polarity (in the range from 0 to 1) of a given opinion. Likewise, the Paralleldots library allows the application of sentiment analysis techniques on texts in different languages, being one of the few libraries that supports the Spanish language. The disadvantage of this library is the limit of requests that can be made per minute, which is why it is necessary to process the opinions in blocks. Finally, the Pandas library allows accessing and processing data from CSV files and Excel spreadsheets.

In relation to aspects such as the management of academic activities by the University, students highlighted the proposed flexibility for the development of academic tasks and the ICT tools suggested for guiding classes in remote attendance. Regarding the conduct of classes in remote attendance, students emphasized the advantages of virtual learning in terms of time optimization and access to recorded lectures; however, they mentioned the need to enhance the training of university professors in the use of technological tools and the adoption of suitable methodologies for virtual instruction. Regarding assessment activities, students emphasized the flexibility and variety of academic tasks. Nevertheless, they mentioned that in different courses, where a set of deliverables was not clearly defined, activities increased and accumulated towards the end of the course. Concerning how students carried out their academic activities, they emphasized the development of time management skills and self-learning as a means to complement the topics covered in class.

Despite the contributions of this study, some limitations must be acknowledged. First, the sample size was limited to 46 students, which may restrict the generalizability of the findings to other academic programs or institutions. Second, the sentiment analysis was conducted using the Paralleldots library, which, while effective, has inherent limitations in processing nuanced emotions and context-dependent sentiments. Future studies could explore alternative sentiment analysis models, such as transformer-based deep learning approaches, to enhance classification accuracy. Additionally, the survey responses were collected at a single point in time, meaning that longitudinal changes in student perceptions remain unexplored.

As a future work derived from the present research, we aim to extrapolate the study to the context of tourism, intending to identify the perception of travelers regarding Colombian tourist sites. Similarly, it is planned to develop an automated sentiment analysis tool in the future, which would allow loading survey data for subsequent statistical and graphical analysis of polarities. Furthermore, the goal is to incorporate into the proposed tool the analysis of word frequency, aiming to enhance the polarity analysis.

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