Automated tool for conducting emotion analysis studies in perception surveys

Gabriel Elías Chanchí Golondrino[1], Manuel Alejandro Ospina Alarcón[1], Claudia Estella Hernandez Londoño[2]
[1]Systems Engineering Program, Faculty of Engineering, University of Cartagena, Cartagena de Indias, Colombia
[2]Chemical Engineering Program, Faculty of Engineering, University of Cartagena, Cartagena de indias, Colombia

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ABSTRACT

Considering the growing need for companies to automate the analysis of customer opinions from different digital media, this paper outlines the development of an automated tool for emotion analysis in survey responses utilizing Ekman's six-emotion model (joy, excitement, anger, sadness, fear, and boredom). The tool processes spreadsheets containing qualitative responses and generates the percentage distribution of emotions at both individual and aggregated levels. A case study conducted with 46 systems engineering students at the University of Cartagena during the COVID-19 pandemic showed that 'anger' was the most prevalent emotion (29.3%), followed by 'excitement' (19.4%), while 'boredom' was the least frequent (2.6%). The tool demonstrated an accuracy rate of 92% in classifying emotions, compared to 90% achieved through manual coding. These results highlight the tool's effectiveness in automating emotion analysis, providing statistical and graphical reports that aid decision-making in academic and organizational contexts.

Corresponding Author:

Gabriel Elías Chanchí Golondrino
Systems Engineering Program, Faculty of Engineering, University of Cartagena
Consulate Avenue 30th Street No. 48–152, Cartagena de Indias, Colombia
Email: gchanchig@unicartagena.edu.co

1. INTRODUCTION

The comments and opinions expressed by the general public in different digital media, being subjective in nature, have great potential for knowledge discovery and play an important role in understanding people's satisfaction and requirements with respect to a particular product, service, or company [1]–[4]. In this sense, in different contexts such as business, the so-called perception questionnaires have been used, which seek to identify the degree of acceptance of a user with respect to a product or service, having as a challenge the analysis of qualitative questions [5]–[9]. Likewise, with the wide diffusion of social networks, these have become an ideal space both for expressing the opinion of users regarding a particular topic, as well as for the collection and extraction of quantitative and value-added information on such opinions [10]–[14].

Since the advances in the field of artificial intelligence and machine learning, one of the emerging areas of engineering and computer science is affective computing [15], [16], which through emotion and/or sentiment analysis techniques can be used to obtain quantitative indicators from subjective information that includes emotional content, as in the case of opinions [17]–[21]. Affective computing is a multidisciplinary research area, in which different interrelated domains (sociology, psychology, computer science, physiology, mathematics, and linguistics) converge [22] and whose objective is the development of systems capable of recognizing, interpreting, processing and simulating human emotions. Thus, these systems must have the ability to: i) detect emotional states from the use of physiological variables; ii) process and classify the data obtained by using machine learning models; and iii) generate responses to the detected emotions through different channels: colors, sounds, and robots [17], [23]–[26]. In the same sense, from the advantages provided by techniques associated with affective computing such as natural language processing (NLP) [27]–[29], in organizations and companies there is a growing need for automated tools that from different data sets with opinions extracted from various sources (social networks, marketing campaigns, and perception surveys, among others), allow the automatic analysis of the perception of users or customers by processing and obtaining the emotions and sentiments associated with the opinions, as well as the statistical and graphical analysis of the results for the analysis of the results, perception surveys, among others), automatically allow the analysis of user or customer perception by processing and obtaining the emotions and sentiments associated with the opinions, as well as the statistical and graphical analysis of the results for decision making, in addition to the prediction of results at the enterprise level [30]–[32].

Different studies have been conducted in the literature regarding the analysis of perception using affective computing techniques. Thus, Gil-Vera [33] propose as a contribution the development of a study of sentiment polarity analysis (positive, negative, and neutral) based on text mining about the perception of housing projects carried out by the organization "TECHO" in Latin America, based on the analysis of 1,000 comments made on the social network Twitter. Saura *et al*. [34] develop a sentiment polarity analysis study (positive, negative, and neutral) on 2204 comments made by Spanish Twitter users regarding the offers published with the hashtag #BlackFriday in November 2017. Golondrino and Cordoba [35] conduct a sentiment and emotion analysis study on the speech of the signing of the peace agreement in Colombia, in such a way that the polarity analysis is performed on the text of the speech, while the emotion analysis is performed on the audio of the speech through the use of the acoustic properties of arousal and valence. Nair *et al*. [36] proposed a sentiment polarity analysis study on the different opinions of Twitter users regarding the COVID-19 pandemic, making use of 3 different machine learning algorithms. Athindran *et al*. [37] conduct a sentiment analysis study to evaluate the perception of Indian twitter users regarding different features of new launches of two smartphone brands: Vivo and Oppo, for which they made use of a Lexicon and Naive Bayes based algorithm. Ikoro *et al*. [38] analyze the polarity of sentiment on the opinions expressed by twitter users in the United Kingdom regarding the UK electricity companies. Shahnaz *et al*. [39] proposed a method for emotion detection, based on the use of electroencephalogram signal waves and a machine learning model based on support vector machine (SVM).

The previous works show the importance of the use of affective computing in different application contexts, in order to obtain quantitative indicators of a user's perception from qualitative data. Despite the above, most of these approaches focus on determining the polarity of the text (positive, negative, and neutral), without addressing the analysis of text emotions, which could enrich the analysis of opinions beyond the three polarities, considering, for example, Ekman's 6-emotion model [40]. In this same sense, it is observed that the works presented focus on the evaluation of different machine learning models, specifically classification models or supervised learning, without addressing the automation of the sentiment or emotion analysis process, in order to facilitate their extrapolation and use of such techniques in different contexts by stackeholders in a transparent manner [30]–[32]. Thus, it is necessary to have tools that, based on qualitative data associated with opinions or perception surveys, enable the analysis of sentiments and emotions, as well as the automatic generation of graphical reports about the distribution of emotions on each opinion and about the consolidated opinions of each question of a survey.

Based on the above, in this article we propose as a contribution the development of an automated tool that takes advantage of the benefits provided by affective computing, for conducting emotion analysis studies in perception surveys, considering the challenges associated with the analysis of qualitative questions. In this way, the tool receives as input a spreadsheet with the answers to different qualitative questions and obtains as a result the percentage distribution of the 6 emotions proposed by Ekman [40] for each opinion, in addition to the consolidated distribution for each question. The proposed tool was validated from the analysis of a perception study conducted in the systems engineering program of the University of Cartagena, regarding the development of academic activities during the confinement caused by COVID-19, in which 5 qualitative questions were asked to students from different semesters. The proposed tool was validated by conducting a perception study in the systems engineering program of the University of Cartagena, regarding the development of academic activities during the confinement caused by COVID-19, in which 5 qualitative questions were asked to students from different semesters.

This study is significant as it addresses a gap in emotion analysis in perception surveys by developing an automated tool that utilizes affective computing techniques. The tool allows for a more nuanced analysis of emotions beyond simple polarity, providing insights into users' emotional responses to qualitative data. This advancement has implications for better understanding user satisfaction and improving decision-making processes based on emotional content.

The remainder of the article is organized as follows: section 2 presents the method employed in the development of this research. Section 3 outlines the results and discussion, where the design and implementation of the automated tool for conducting an emotion analysis study in perception surveys are described, along with a case study that validated the proposed automated tool presented in this article. Finally, section 4 presents the conclusions and future work derived from this research.

2. METHOD

For the development of this research, four methodological phases were considered, namely: exploration of tools and technologies for emotion analysis, as well as for statistical analysis and visualization of the results; design of the automated tool for emotion analysis; construction of the automated tool for emotion analysis; and execution of the case study (see Figure 1). According to the Figure 1, the method employed in this study consists of several distinct phases. Initially, we conducted a comprehensive review of existing emotion analysis tools to identify the most suitable approaches for our specific context. Following this, we designed a survey to capture the emotional responses of participants using a Likert scale. The data collected from the survey was then processed using a custom-built software tool that automates the emotion analysis process. This tool incorporates NLP techniques to analyze the text responses and classify them according to predefined emotional categories. The final phase involved statistical analysis to validate the reliability and accuracy of the tool's classifications, comparing them against manual coding conducted by human analysts.

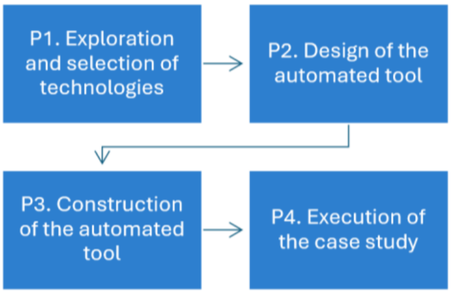

Figure 1. Method considered

In Phase 1, a set of technologies and libraries were explored and selected for both the obtaining of emotions on the dataset opinions using an adaptation of Ekman's 6-emotion model (happy, excited, anger, sad, fear, and bored) [40], and for the statistical and graphical analysis of the distribution of emotions per opinion and at the dataset level. In Phase 2, the design of the functional modules that allow the extraction of emotions from the opinions and the analysis of the results obtained in a statistical and graphical way was carried out. In Phase 3, based on the functional modules designed and the tools selected, the automated tool that makes it possible to conduct emotion analysis studies in perception surveys was built. Finally, in Phase 4, based on the use of the constructed tool, the opinions obtained in a perception study conducted within the systems engineering program of the University of Cartagena, regarding the development of academic activities during the confinement caused by COVID-19 were analyzed, in which 5 qualitative questions were asked to a total of 46 students from different semesters of the program.

3. RESULTS AND DISCUSSION

The design and implementation of the automated tool for the analysis of emotions in perception surveys is described below. At the design level, a diagram is presented with the main modules that make up the tool, as well as the architecture of the tool and the different processes that are developed in its 3 layers (view, analysis, and storage). Similarly, at the implementation level, the different graphical interfaces that make up the automated tool are described. Thus, Figure 2 shows the 5 functional modules that make up the automated tool: graphical user interface (GUI) module, emotion analysis module, statistical analysis module, graphics module, and reports module.

The GUI module is responsible for managing the different graphical components that are included in the tool interface (tabs, panels, text boxes, text areas, and buttons), as well as the management of events related to the interaction between the user and the interface components. In the case of the developed tool, this module was implemented using the Python Tkinter library and its associated sub-components, which allow the generation of the tool interface. From the survey data loaded by the user in the graphical interface, using the emotion analysis module, it is possible to obtain the distribution of the 6 emotions of the Ekman model for each of the opinions with respect to a given question of the loaded survey. For the above, the functionalities provided by the Python pandas and paralleldots libraries were used. Once the analysis of emotions has been performed for each of the opinions of the loaded survey, the report module allows the generation of a .csv report with the distribution of emotions for each opinion of a given question. Similarly, when the analysis of emotions for the different opinions is finished, the statistical analysis module allows to obtain statistical measures (average, standard deviation, minimum value, and maximum value) on the different emotions obtained for the opinions of a given question. The was accomplished through the mathematical and statistical functions provided by the numpy Python library. Finally, through the graphs module it is possible to visualize the distribution of emotions for each of the opinions, as well as the percentage distribution of emotions in each question. The above graphs were generated in the tool using the Python matplotlib library. Figure 3 shows the architecture of the tool and the different processes that compose the layers of the architecture (view, analysis, and storage) and specifies the functional modules described in Figure 2.

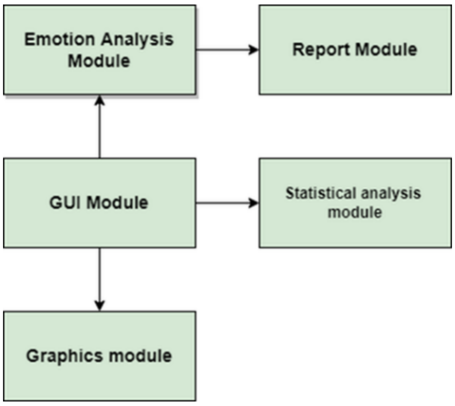

Figure 2. Functional modules of the tool

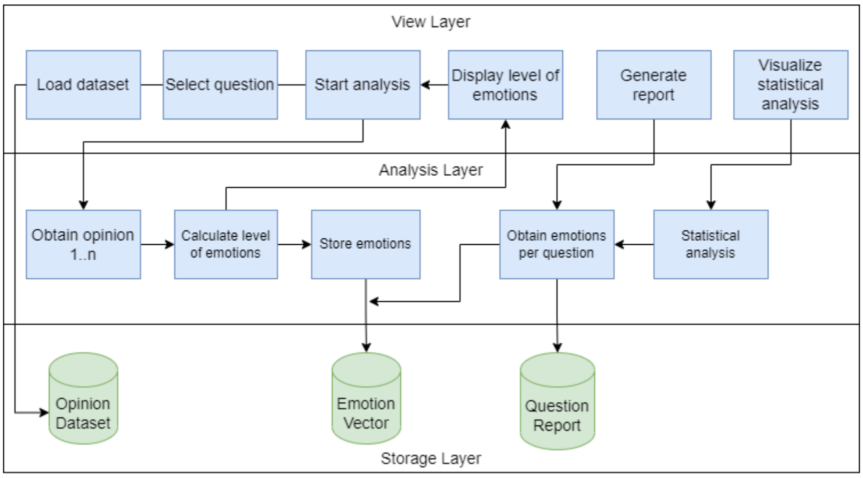

Figure 3. Architecture of the automated tool

The view layer comprises the graphical interfaces of the automated tool, so that in the first instance it is possible to load the dataset with the opinions of a given survey and choose the question of the survey to be processed, and then start the emotion analysis. In this sense, it is worth mentioning that the tool has been designed to analyze the answers given to different qualitative questions in a perception survey. In the analysis layer, the different opinions of the selected question are processed one by one using the Python pandas library and the distribution of the 6 emotions of the Ekman model is obtained in each opinion using the Python paralleldots library, so that once these emotions are obtained, they are temporarily stored in a Python list or vector data structure, while the results of the analysis of each opinion are shown to the user. At the end of the analysis of the different opinions of a question, from the view layer the user can generate a report with the analysis, for which the queries are made to the temporal vector of emotions and a .csv file is generated containing the different opinions and the distribution of the 6 emotions considered in each one of them. Similarly, from the view layer, the user can visualize the statistical analysis at a mathematical and graphical level on the emotions of the different opinions of a given question, making use respectively of the Python pandas and matplotlib libraries. At the mathematical level, the tool allows to obtain statistical measures such as the average, standard deviation, minimum value and maximum value, on the distribution of each of the emotions in the analyzed opinions. Likewise, at a graphic level, it is possible to visualize the specific distribution of the 6 emotions in each of the opinions and over the total number of opinions. Based on the diagram of functional modules and the different processes of each of the layers of the architecture, the automated tool for the analysis of emotions in perception surveys was implemented, whose main graphical interface is shown in Figure 4. The graphical interface of the tool was implemented using the components provided by the Tkinter library and consists of four tabs: "Process Questions", "Statistical Analysis", "Graphical Analysis", and "General Analysis".

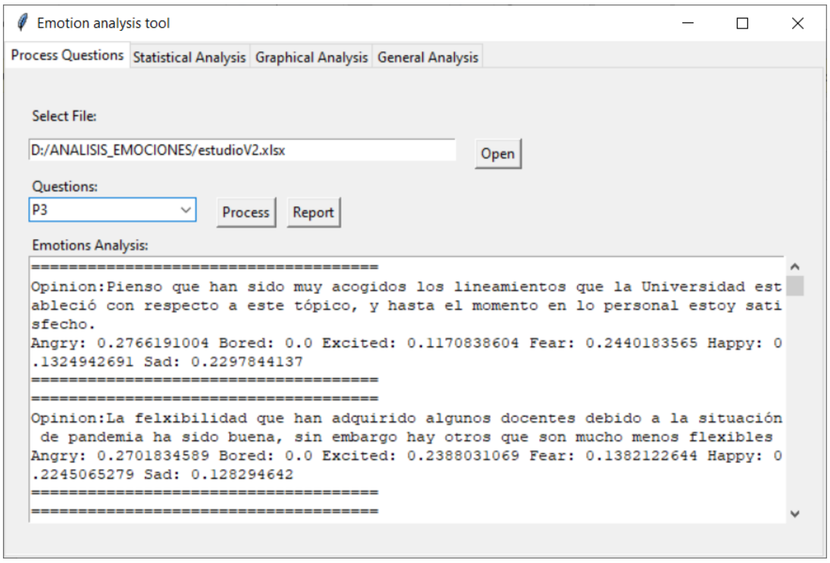

Figure 4. Main graphical interface of the tool

In the "Process Questions" tab, in the first instance, by pressing the "Open" button and making use of the Python pandas library, an Excel file is loaded with the opinions of the perception survey. Once the file has been uploaded to the tool, the question on which the opinions will be analyzed is selected from the selection list, so that once the "Process" button has been pressed, the analysis of the distribution of the 6 emotions on each of the opinions of the selected question is started. This distribution corresponds to the level of participation of each of the emotions in the analyzed opinion, so that the sum of these levels is equal to 1. Thus, as an example for the first opinion presented in Figure 4, the distribution levels of opinions were: angry=0.276, bored=0, excited=0.117, fear=0.244, happy=0.132, and sad=0.229. Once the analysis of emotions on the opinions of the selected question is finished, it is possible to generate a report of the analysis by pressing the "Report" button. When the analysis of the opinions is completed, the other tabs of the tool are automatically enabled. Figure 5 shows the interface corresponding to the "Statistical Analysis" tab, which presents the statistical results on the emotions corresponding to the different opinions of the question selected in the "Process Questions" tab. Thus, Figure 5 shows the statistical measures of: average, standard deviation, minimum value and maximum value for the values obtained in each of the 6 emotions considered over the total number of opinions. As an example, in Figure 5 for the emotion "Angry" an average distribution value of 0.293, a standard deviation of 0.103, a minimum distribution value of 0.061 and a maximum distribution value of 0.536 were obtained.

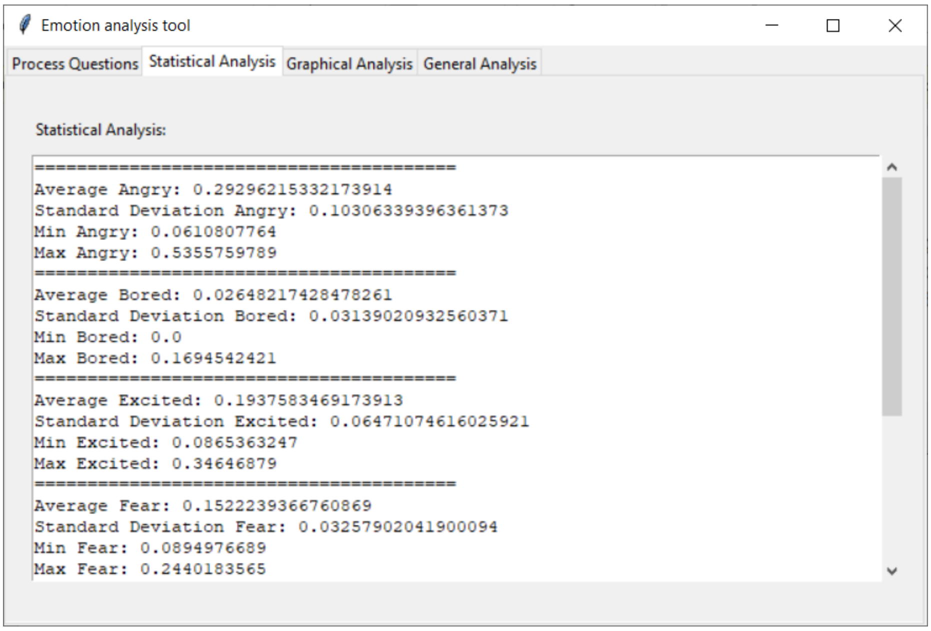

Figure 5. “Statistical analysis” tab of the tool

Figure 6 shows the interface associated with the "Graphical Analysis" tab, which shows the distribution of emotions in all the opinions corresponding to the question analyzed. As an example, Figure 6 shows the bar chart generated from the analysis of a question containing 46 opinions. Thus, it is possible to see graphically how, according to Figure 6, the dominant emotions or those that are presented in the highest percentage in the 46 opinions are angry, excited and happy.

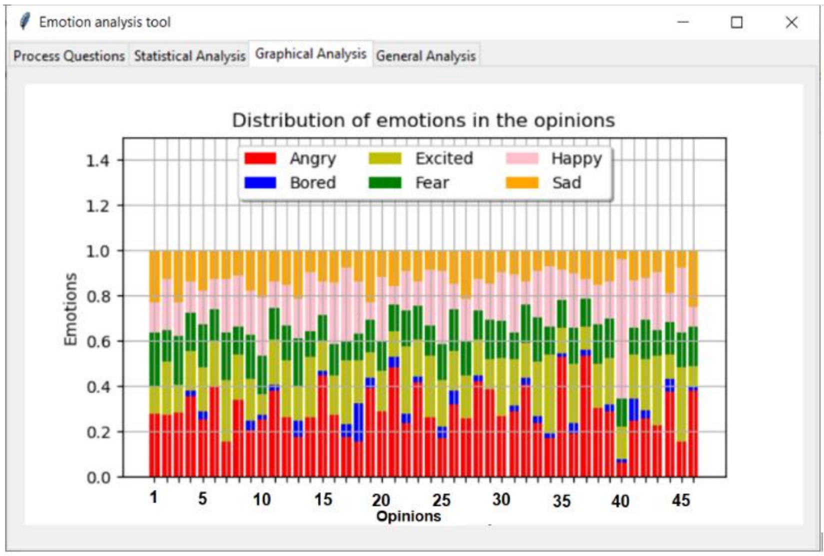

Figure 6. “Graphical analysis" tab of the tool

Finally, Figure 7 shows the graphic interface corresponding to the "General Analysis" tab, in which a pie chart shows the percentage distribution of emotions over the consolidated opinions associated with the question selected in the "Process Questions" tab. Thus, Figure 7 shows how by consolidating the distribution of the emotions of the 46 opinions of the example in Figure 6, it is possible to obtain that the emotion with the highest percentage of presence in the opinions is "Angry" with 29.3%, while the emotion with the lowest presence in the opinions is Bored with 2.6%. In order to verify the functionality of the tool, a case study was developed in which the analysis of emotions was performed on the results of a perception survey conducted to 46 students of the systems engineering program at the University of Cartagena, which included 5 qualitative questions related to the development of academic activities during the remote presence originated by the COVID-19 pandemic. Table 1 shows the questions considered in the perception survey.

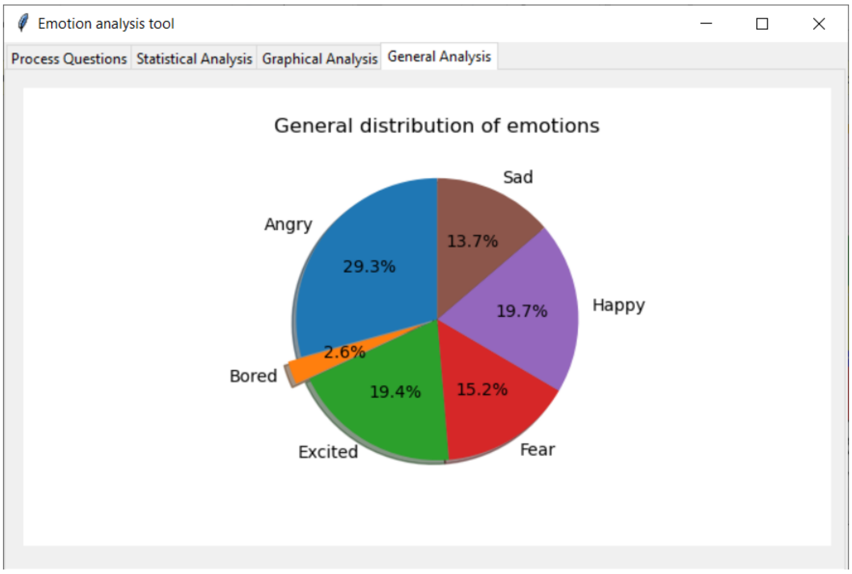

Figure 7. “Graphical analysis" tab of the tool

Table 1. List of case study questions

Id	Question
1	What is your opinion about the way in which the University has been managing the different academic processes during remote presence?
2	What do you think about the way in which remote presence classes have been developed within the University?
3	What is your opinion regarding the way in which the evaluation activities have been carried out in the different courses?
4	How have you been organizing and carrying out your academic activities to effectively achieve the course objectives?
5	Do you consider that remote presence has affected the quality of university education? Justify your answer

From the reports generated by the tool, Figure 8 shows the distribution of the 6 emotions in a range from 0 to 1 for each of the opinions associated with the 5 questions analyzed. From Figure 8, it can be observed that for question 1, related to the management of processes by the University, the emotions "Angry" and "Excited" are the most present in the different opinions (25.4% and 20.9% respectively), while the emotion "Bored" is the least present (4.1%). With respect to question 2, which relates the way in which the classes were developed during the pandemic, the emotions that have a greater presence in the opinions are "Angry" and "Excited" (24.8% and 21.8% respectively), while the emotion "Bored" is the one that is presented to a lesser extent (4.5%). Regarding question 3, which involves the way in which the evaluations were carried out during remote presence, the emotions with the highest presence in the opinions are "Angry" and "Happy" (29.3% and 19.7% respectively), while the emotion with the lowest presence is "Bored" (2.6%). In question 4, related to the organization in the development of academic activities, the emotions "Angry" and "Excited" had the highest presence in the opinions (27.8% and 21% respectively), while the emotion "Bored" is the one with the lowest presence (3.2%). Finally, in question 5, associated with the impact on the quality of remote presence, the emotions with the highest presence are "Angry" and "Excited" (30.6% and 18.4% respectively), while the emotion with the lowest presence is "Bored" (2.3%). This can be seen more clearly in the percentage distribution values by emotion and by type of emotion (positive and negative) shown in Table 2. In this sense, if the percentages of emotions considered positive ("Excited" and "Happy") and the percentages of emotions considered negative ("Angry", "Bored", "Fear", and "Sad") according to Russell's model are taken together, it is possible to observe in Table 2, how the questions with the highest percentage of negative emotion were question 3 (%Negative=60.8%) and question 5 (%Negative=64.4%), while the questions with the highest percentage of positive emotion were 2 (%Positive=41.9%) and 4 (%Positive=40.6%).

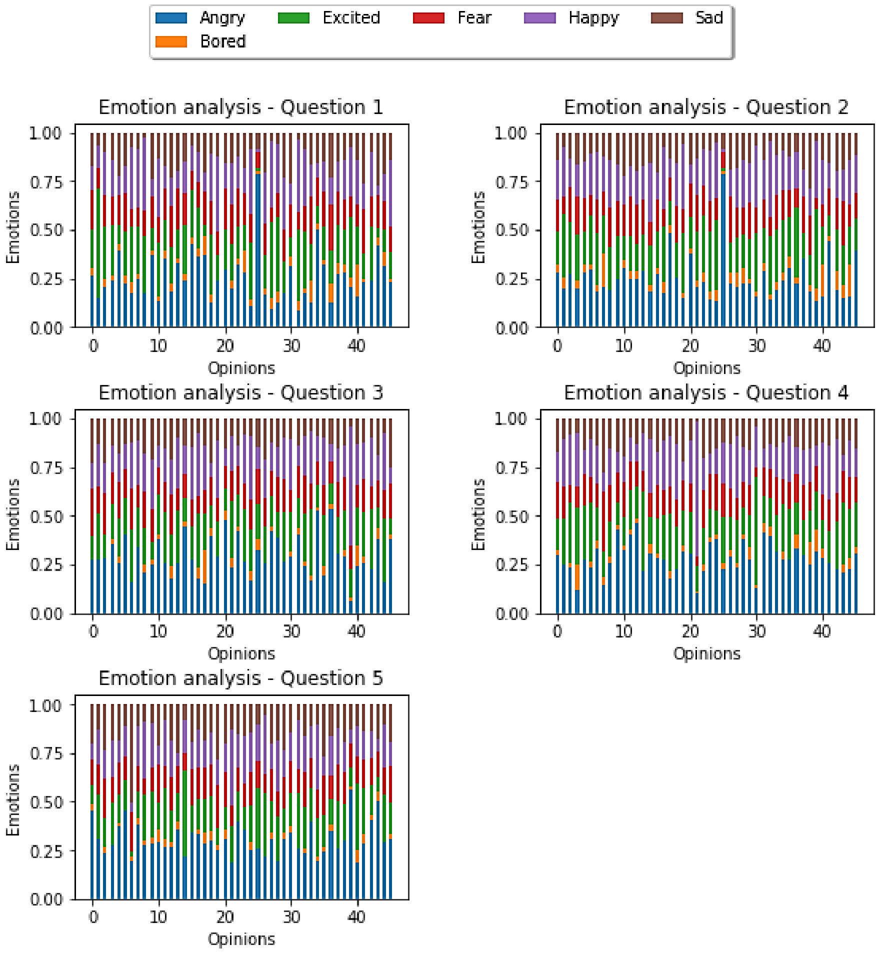

Figure 8. Distribution of emotions in the case study

This article proposes the design and development of an automated tool for conducting emotion analysis studies on perception surveys. The tool can be highly useful for obtaining the distribution of emotions in an opinion regarding a product, service, or academic context, or a similar context. This tool enables the extraction of quantitative value from the subjectivity of an opinion. An advantage of the proposed tool is that, by utilizing libraries with pre-trained models, it abstracts the process of emotion analysis and detection, allowing any end user to leverage the benefits of affective computing without implementing or evaluating different artificial intelligence models, as done in [36], [39]. As a result, it is possible to extrapolate this approach to the analysis of perception questionnaires independently of the sample size. In other words, there is no need to train models with extensive datasets as provided by social networks. Additionally, the proposal presented in this article enhances affective computing analysis. In contrast to studies in [33], [34], [37], which focus on polarity analysis (positive, negative, and neutral), the current study obtains the distribution of emotions in an opinion following the model of 6 emotions proposed by Ekman [40]. This allows survey analysts to have a clearer idea of what the user is perceiving regarding a topic, product, or service and enables the identification of specific emotions such as excitement, fear, and boredom, leading to more actionable insights. This enhanced granularity allows for a more comprehensive analysis of user perceptions, which could be particularly valuable for organizations seeking to fine-tune their responses based on nuanced emotional feedback.

The results obtained from the automated tool were consistent with the manual coding, demonstrating a high degree of accuracy in emotion classification. Specifically, the tool achieved an accuracy rate of 92%, which was comparable to the 90% accuracy rate obtained through manual coding. These findings suggest that the automated tool is highly reliable for conducting emotion analysis in perception surveys. Furthermore, the statistical analysis revealed significant correlations between certain emotional categories and demographic variables, such as age and gender, providing insights into the factors that influence emotional responses.

These results are discussed in the context of existing literature, highlighting the tool's potential applications in broader research settings.

Table 2. Emotion analysis results of the case study

Id	Statistical measures	% Emotions (%)
Question 1	Angry: average: 0.254, min: 0.09, and max: 0.787. Bored: average: 0.04, min: 0, and max: 0.169. Excited: average: 0.209, min: 0.02, and max: 0.563. Fear: average: 0.154, min: 0.08, and max: 0.248. Happy: average: 0.195, min: 0.017, and max: 0.38. Sad: average: 0.146, min: 0.028, and max: 0.273.	Angry: 25.4 Bored: 4.1 Excited: 20.9 Fear: 15.4 Happy: 19.5 Sad: 14.6 %Pos=40.4 %Neg=59.5
Question 2	Angry: average: 0.248, min: 0.133, and max: 0.787. Bored: average: 0.045, min: 0, and max: 0.169. Excited: average: 0.217, min: 0.022, and max: 0.409. Fear: average: 0.152, min: 0.061, and max: 0.234. Happy: average: 0.200, min: 0.017, and max: 0.388. Sad: average: 0.137, min: 0.042, and max: 0.291.	Angry: 24.8 Bored: 4.5% Excited: 21.8 Fear: 15.2 Happy: 20.1 Sad: 13.7 %Pos=41.9 %Neg=58.2
Question 3	Angry: average: 0.293, min: 0.061, and max: 0.536. Bored: average: 0.026, min: 0, and max: 0.169. Excited: average: 0.194, min: 0.086, and max: 0.346. Fear: average: 0.152, min: 0.089, and max: 0.244. Happy: average: 0.197, min: 0.077, and max: 0.617. Sad: average: 0.137, min: 0.038, and max: 0.251.	Angry: 29.3 Bored: 2.6 Excited: 19.4 Fear: 15.2 Happy: 19.7 Sad: 13.7 %Pos=39.1 %Neg=60.8
Question 4	Angry: average: 0.278, min: 0.105, and max: 0.462. Bored: average: 0.032, min: 0, and max: 0.134. Excited: average: 0.209, min: 0.115, and max: 0.552. Fear: average: 0.148, min: 0.048, and max: 0.038. Happy: average: 0.196, min: 0.075, and max: 0.692. Sad: average: 0.136, min: 0.021, and max: 0.277.	Angry: 27.8 Bored: 3.2 Excited: 21 Fear: 14.8 Happy: 19.6 Sad: 13.6 %Pos=40.6 %Neg=59.4
Question 5	Angry: average: 0.306, min: 0.184, and max: 0.561. Bored: average: 0.023, min: 0, and max: 0.068. Excited: average: 0.184, min: 0.025, and max: 0.434. Fear: average: 0.150, min: 0.082, and max: 0.223. Happy: average: 0.172, min: 0.042, and max: 0.387. Sad: average: 0.164, min: 0.058, and max: 0.507.	Angry: 30.6 Bored: 2.3 Excited: 18.4 Fear: 15.1 Happy: 17.2 Sad: 16.4 %Pos=35.6 %Neg=64.4

The proposed study introduces a novel automated tool designed for conducting emotion analysis studies on perception surveys. This tool is a significant advancement over traditional methods of emotion analysis. It leverages the principles of affective computing to extract and analyze emotions from qualitative survey responses, offering a more detailed understanding of user sentiments beyond simple polarity classifications.

It is important to clarify that the tool represents a novel contribution. The development of this tool is a central aspect of this research. As detailed in the method section, the tool was designed, built and validated to automate the process of analyzing emotions in perception surveys, and this section delves into the functionality of the tool, its implementation and the case study used to validate its effectiveness.

It should be noted that the initial validation of the proposed tool was conducted with a sample of 46 respondents from the entrepreneurship fair, which may limit the generalizability of the findings to a broader population. However, the tool was designed with scalability in mind, utilizing robust open-source technologies such as NumPy, Pandas, and Matplotlib. These technologies ensure the tool’s ability to process larger datasets efficiently by automating the analysis of emotion distributions from qualitative responses, regardless of sample size. The tool can handle larger samples by processing .csv files of varying sizes, generating detailed statistical and graphical reports without compromising accuracy or performance. Future validation studies with samples exceeding 100 participants will provide further insights into the tool’s applicability in diverse settings and strengthen the generalizability of the results across different contexts. This will ensure that the tool’s findings are representative and robust in a wide range of applications.

4. CONCLUSION

In this paper, we presented the development of an automated tool for emotion analysis in survey responses, utilizing Ekman's six-emotion model to address the increasing need for companies to automate customer feedback analysis from digital media. Our findings showed that "anger" and "excitement" were the most frequent emotions among university students during the COVID-19 pandemic, while "boredom" was the least expressed. The tool achieved an accuracy rate of 92%, demonstrating its efficacy in emotion classification and its potential for use in both academic and organizational contexts.

Although manual methods can be employed for emotion detection, our tool significantly reduces time and effort, offering real-time reports and graphical outputs that aid in decision-making processes. This supports our claim that automation in emotion analysis not only enhances efficiency but also provides deeper insights into user emotions. Critics may argue that emotion detection remains subjective; however, the tool's high accuracy suggests that it is a valuable asset in standardizing emotion analysis. Future research could focus on expanding the model to include more nuanced emotions and applying the tool across different domains and populations. Further validation studies are necessary to ensure the robustness of the tool in more diverse settings, and improvements in the user interface can increase its accessibility for non-technical users.

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BIOGRAPHIES OF AUTHORS

Gabriel Elías Chanchí Golondrino received the B.S degree in electronics and telecommunications engineering in 2008, the master in telematics engineering in 2013 and his PhD in telematics engineering in 2017 at the Universidad del Cauca–Colombia. He is currently professor and researcher in the University of Cartagena, Colombia. His research interests include human computer interaction, affective computing, machine learning, and internet of things. He can be contacted at email: gchanchig@unicartagena.edu.co.

Manuel Alejandro Ospina Alarcón received the B.S. degree in control engineering in 2006, the master of engineering-materials and processes degree in 2009 and his Ph.D. in engineering–science and technology of materials with emphasis on phenomenological modelling and simulation of industrial processes in 2015 at the Universidad Nacional de Colombia. He is currently professor and researcher in the University of Cartagena, Colombia. His research interests include phenomenological theory using first principles, identification of dynamical systems, and intelligent systems. He can be contacted at email: mospinaa@unicartagena.edu.co.

Claudia Estella Hernandez Londoño received the B.S. degree in chemical engineering in 2013, the master in biological sciences in 2010 and her Ph.D. in engineering with emphasis on chemical engineering in 2017 at the Universidad Nacional de Colombia. Her research interests include characterization and value generation of bee products, modeling and data analysis, biotechnology and nanotechnology, entrepreneurship, and innovation. She can be contacted at email: chernandezl@unicartagena.edu.co.