SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 5, (2026), pp. 2054-2062
Open Access. Online & Print

DOI: 10.5281/zenodo.21301237

CREATING A TAILORED MOBILE APP FOR EMOTION DETECTION IN REFLECTIVE REPORTS OF UNDERGRADUATE MEDICAL STUDENTS: DEVELOPMENTAL STRATEGIES

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Received: 03/04/2026
Accepted: 09/05/2026

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ABSTRACT

Reflective reports are increasingly used in medical education to enhance student learning and professional development. Analysing the sentiments and emotions within these reports provides valuable insights into students' attitudes, empathy, and emotional intelligence. With advancements in natural language processing (NLP) and mobile technologies, there is potential to automate this analysis, making it more efficient and consistent. This study aimed to develop a mobile application capable of detecting and classifying emotions in reflective reports of undergraduate medical students, thereby supporting educators in assessing both reflective content and emotional engagement. An Android-based mobile application was developed using Android Studio (XML for UI design, Java for backend). The NRC Word-Emotion Association Lexicon (EmoLex) was integrated to classify eight primary emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and sentiments (positive, negative). Reflective reports written by Year 1 medical students following a workshop on online sexual harassment served as input. The app extracted text from uploaded Word documents, tokenized words, matched them against the lexicon, and visualized results using bar charts. Both local (document-specific) and global (cumulative) emotion profiles were generated. The application successfully identified and quantified emotions across student reflections. For instance, one document exhibited predominantly negative emotions (anger 50.0%, surprise 35.7%), while another reflected positive tones (trust 66.7%, joy 16.7%). The user interface enabled secure login, file uploads, emotion analysis, and summary visualization. In conclusion, our mobile app provides a user-friendly, automated tool for emotion detection in reflective reports, integrating qualitative and emotional analysis. It offers real-time feedback, supports evidence-based educational strategies, and enhances understanding of students' emotional intelligence. Future work should refine algorithms to capture nuanced emotions and expand applicability across broader educational contexts.

KEYWORDS: Reflective Practice, Mobile Application, Sentiment Analysis, Medical Education, Emotion Detection.

1. INTRODUCTION

Qualitative assessment methods offer a holistic, integrated approach to evaluating abilities, interests, and personality traits (1). These methods provide a more active role for students and better adaptability to individual differences than standardized tests (1). Qualitative approaches, grounded in constructivist epistemologies, serve as alternatives to empirical practice models in social work (2). They are valuable tools for developing in-depth understandings of phenomena and contexts in institutional assessment (3). Qualitative techniques are beneficial for assessing diverse institutional cultures, student trajectories, and teaching effectiveness (4,5). These methods, including informal interviews, case studies, and direct observation, complement quantitative assessment methods (6). While qualitative methods offer numerous advantages, practitioners may face practical difficulties in implementation. Nonetheless, their ability to provide rich, contextual data makes them invaluable in various assessment contexts.

Reflective report is an example of qualitative assessment and has gained increasing importance in medical education as a tool to enhance student learning and professional development (7,8). It involves analytical thinking about actions, incidents, or situations, fostering deeper understanding and improvement (9). It also allows the students to analyse their clinical experiences, identify areas for improvement, and develop a deeper understanding of patient care (8). Various methods have been employed to facilitate reflection, including written or web-based portfolios. However, challenges exist in implementing reflective practice effectively, such as clarifying its purpose to students and ensuring educator modelling of reflective behaviours (10). Recent research has highlighted the potential of reflective practices to develop social responsibility and consciousness among medical students (11). Despite its recognized value, introducing and assessing reflective practice in medical curricula remains complex, with ongoing exploration of optimal approaches and timing. Overall, reflective practice is considered a crucial skill for medical students to acquire and nurture throughout their professional development.

Another important outcome of analysing a reflective report is to gauge the sentiments and emotions of the student. This can be done by sentiment/emotion analysis, by which the subjective feelings expressed by the student can be categorized into positive, negative, or neutral, as well as studying the emotions expressed by the students, such as the basic eight emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust). This can provide insights into attitudes, behaviour, and opinions of an individual in a particular context or topic. There are mainly three ways of analysing sentiments/emotions in a text: lexicon-based analysis, machine learning techniques, and network analysis. Lexicon-based analysis involves using a list of words or phrases associated with a particular sentiment or emotion and matching it to words or phrases in the text. Thus, a good lexical resource is vital for accurate classification of sentiment or emotion (12).

With the rise of mobile technologies and advancements in natural language processing (NLP), there is an opportunity to enhance the assessment processes through automation (13). Mobile applications are increasingly being adopted in educational settings, offering new opportunities for learning and access to course information. These apps can enhance interactivity and effectiveness in teaching, potentially bringing quality education to a wider audience (14). However, developing educational apps requires careful consideration of strategies, tools, and business models (15). A mobile application that performs qualitative analysis of reflective reports offers a solution to streamline evaluations while providing objective insights into students' reflections. Beyond standard qualitative assessment, emotion analysis through these mobile apps can provide significant value, as they reveal students' emotional engagement and empathetic responses to their clinical experiences.

This research focuses on the development of a mobile app specifically designed to detect and classify emotions within the reflective text, enabling a more comprehensive evaluation of students' emotional intelligence. By automating the qualitative assessment and emotional classification, this tool aims to provide educators with consistent, real-time feedback while supporting students in their reflective learning journey.

2. METHODS

To identify different types of emotions, such as anger, fear, anticipation, trust, surprise, sadness, joy, and disgust in the reflective report, a software program was developed.

Software development took into consideration the following steps:

2.1. Input

As part of the medical curriculum, Year 1 students undergo a workshop on “Freedom of expression in social media”. The main objective of this workshop is for the students to recognize online sexual harassment and actions they can take to avoid or tackle online sexual harassment. After the workshop, the students are required to write and submit a reflective report on their opinion and any personal experiences on freedom of expression in social media in the context of online sexual harassment, and what they would do if they knew someone was sexually harassed online. These reflective reports were anonymized and were used as the input to analyse the sentiment and emotions as perceived by the students.

2.2. Identification of Related Symptoms

This step involves text analysis, whereby semantic similarities between words will be captured. In this study, we used the NRC Word-Emotion Association Lexicon (aka EmoLex). The NRC Emotion Lexicon is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust). The annotations were manually done by crowdsourcing. This database can be used freely for non-commercial research and educational purposes (16,17).

2.3. Computation and Summarization

2.3.1. Hardware and Software

The application was developed using the latest version of Android Studio, employing XML for user interface design and Java for backend programming. Development and testing were conducted on a system equipped with an Intel Core i7 processor and 16 GB of RAM, ensuring efficient performance during compilation and execution. The application was tested on a Samsung Android device to validate its functionality in a real-world environment.

2.3.2. Interface Design and Functionalities

The application's architecture centers around the Main Activity, which orchestrates the emotion analysis workflow. Upon launch, the application initializes the user interface, configures a bar chart for emotion visualization, sets up file picker functionality, and loads an emotion lexicon from the application's assets. Users can upload .docx documents via the interface, which are then parsed and processed word by word. Each word is compared against entries in the predefined emotion lexicon to identify and count occurrences of specific emotions. The analysis results are presented both numerically and through dynamically rendered bar charts for intuitive visual interpretation.

2.3.4. Arithmetic Workflow

1. Initialize Activity: The on Create () method binds all UI components, sets up the chart for emotion display, initializes the file picker, and loads the lexicon file from the app's assets.
2. Handle File Upload: On clicking the upload Button, the open File Chooser () method is invoked to enable users to select a .docx file from their device.
3. Perform Analysis: Clicking the analyze Button triggers the perform Local Analysis () method, which:
   - Extracts and reads text content from the uploaded document.
   - Matches words with entries in the emotion lexicon.
   - Tallies local emotion counts.
   - Displays results both numerically and as a bar chart.
4. Generate Summary: The summary Button activates display Emotion Summary and Chart (), which aggregates results across multiple sessions/files and displays an overall emotion profile using a summary bar chart.
5. Navigation and Exit: Pressing the back Button triggers show Exit Confirmation Dialog () to confirm and execute navigation to the Front Activity.
6. Chart Configuration: setup Chart () defines the visual attributes of the bar chart including axis properties, color schemes, and animation effects.
7. Exit Dialog; show Exit Confirmation Dialog () presents users with an option to return to the previous screen.
8. File Picker: open File Chooser () launches the Android file selection interface.
9. Local Analysis Execution: perform Local Analysis () processes the document, computes emotion frequencies, and updates the interface accordingly.
10. Emotion Variable Management: update Emotion Variables () adjusts global emotion counters based on analysis results.
11. Display Local Counts: display Local Emotion Counts Horizontal () prepares the interface for displaying local emotion counts (though currently underdeveloped).
12. Bar Chart Generation: generate Bar Chart () constructs and renders a visual representation of emotion data.
13. Summary Display: display Emotion Summary and Chart () organize and displays the overall emotion data in the application.
14. Overall Summary Display: display Overall Emotion Summary Horizontal () outputs the

aggregate emotion counts.

15. Formatted Chart Display: generate Summary Bar Chart with Positive Values () renders a positive-valued bar chart to enhance clarity.
16. Percentage Formatting: Percentage Value Formatter formats numerical values in the bar chart as percentages.
17. Interactive Feedback: Custom Marker View enables users to tap on bars to reveal exact emotion values.
18. Reset Functionality: clear Summary () resets all charts, summaries, and global variables to their initial state.

2.4. Emotion Analysis and Methods

The application employs a lexicon-based emotion classification approach, utilizing a predefined list of emotions and their associated indicative words. This lexicon, stored in a plain text file named emotion_lexicon.txt within the application's assets, encompasses eight primary emotions: Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger, and Anticipation. The lexicon is dynamically loaded during the application's initialization phase.

When a user uploads a Word document for analysis, the perform Local Analysis () function is triggered. It begins by extracting the textual content from the uploaded .docx file. The text is then tokenized into individual words and normalized to lowercase to facilitate case-insensitive matching.

The classification algorithm operates through a nested iteration mechanism. Each word from the document is compared against the entries in the emotion lexicon. If a match is found between a document word and any emotion-linked term in the lexicon, the corresponding emotion's counter is incremented.

The application maintains two levels of emotion tracking:

- Local Emotion Counters: Represent the emotional content within the currently analyzed document.
- Global (Cumulative) Emotion Counters: Aggregate emotional frequencies across multiple documents analyzed during the session.

Following the analysis, the emotional distribution for the document is visualized using the MPAndroid Chart library. A bar chart is generated to present the frequency of each emotion detected in the uploaded file. Additionally, a summary bar chart displays the cumulative emotion data across all previously analyzed files.

2.5. User Interface Overview

The mobile application initiates with an aesthetically designed front page, featuring the welcoming tagline: "Catch the vibe from our students!" (Figure 1a). This interface includes a prominently placed "Let's Try" button, which serves as an entry point, guiding users into the secure login environment. The login page (Figure 1b) prompts users to input a valid username and password, ensuring authenticated access to the emotional analysis module. This step maintains user privacy and supports secure data handling practices. Upon successful login, users are directed to the core component of the application the Emotional Analysis Page shown in the Figure 1 & 2.

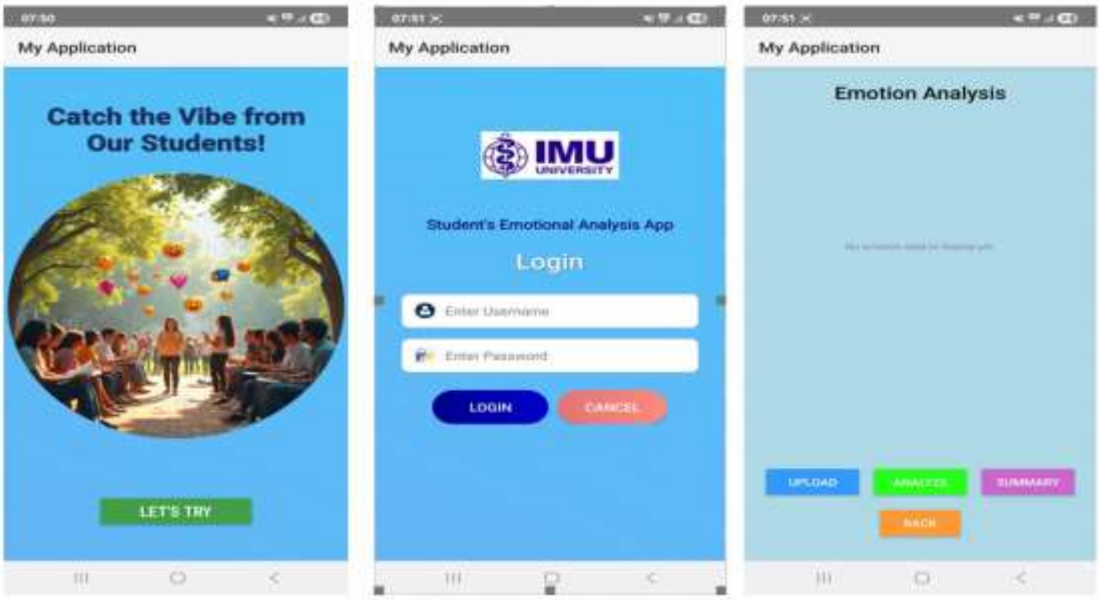

Figure 1: System Interface.

Figure 2: Analysis Summary.

This interactive interface provides four key functionalities, each represented by a dedicated button:

1. Upload – Facilitates file selection from the device's local storage.
2. Analyze – Initiates emotional analysis of the uploaded document.
3. Summary – Presents a cumulative view of emotional findings across analyzed documents.
4. Back – Returns the user to the front page for navigation flexibility.

The Upload button enables users to select a .docx file via the system's file browser. Once selected, the file is prepared for processing. By clicking the Analyze button, the application parses the document content and cross-references it against the predefined emotion lexicon, which encompasses eight primary emotions and approximately 14,500 associated synonym terms.

Each detected emotional word contributes to a frequency count that is subsequently visualized using a bar chart, generated via the MPAndroidChart library. This chart presents the proportion of each emotion as a percentage of the total emotional word count, offering an intuitive and insightful representation of the document's emotional tone. Figure 2a, 2b and 2c shows the app display of the emotion analysis of two sample files along with the summary chart. The application supports continuous analysis, allowing users to upload and process multiple documents within the same session. The Summary button consolidates emotional data from all previously analyzed documents, generating a unified summary bar chart that captures the overall emotional distribution. The Back button facilitates easy navigation by returning users to the application's front page.

3. RESULTS AND DISCUSSION

To evaluate the effectiveness of the emotion detection application, two sample Word documents (Sample1.docx and Sample2.docx) were analyzed using the lexicon-based emotional analysis system developed within the Android environment. The application utilizes a predefined emotion lexicon comprising eight primary emotions: Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger, and Anticipation, with over 14,500 associated synonym terms. The tool scans the textual content of the uploaded .docx files, matches the words against the lexicon, and computes the relative frequencies of each emotion. The results are displayed as percentage distributions and visualized through bar charts for interpretability. The following tables present the percentage-based emotional analysis of each sample document, followed by a consolidated summary that merges the findings from both files.

The emotional analysis of Sample1.docx reveals a dominant presence of Anger, accounting for 50.0% of the total emotional content. This suggests that the document contains a significant number of emotionally charged terms associated with frustration, hostility, or dissatisfaction. The second most prevalent emotion is Surprise at 35.7%, indicating an element of unexpectedness or sudden changes reflected in the text. Both Sadness and Trust are minimally represented at 7.1% each, suggesting occasional references to loss, disappointment, or confidence, but not forming the core emotional tone of the document. Overall, the document exhibits a negative emotional leaning with a mixture of emotional volatility (Table 1).

Table I: Sample File-1 Emotional Analysis Report.

Sl.no	Emotions List	Percentage
1	Joy	00.0
2	Trust	07.1
3	Fear	00.0
4	Surprise	35.7
5	Sadness	07.1
6	Disgust	00.0
7	Anger	50.0
8	Anticipation	00.0

In Sample2.docx, the emotional profile contrasts sharply with that of Sample1.docx. Trust emerges as the most dominant emotion, making up 66.7% of the detected emotional expressions. This suggests a high level of positivity, confidence, and reliability within the content. Both Anticipation and Joy appear equally at 16.7%, reflecting forward-looking optimism and happiness, respectively. The emotional tone of this document is overwhelmingly positive and constructive, which may indicate content that is hopeful, motivational, or supportive in nature (Table 2).

Table 2: Sample File-2 Emotional Analysis Report.

Sl.no	Emotions List	Percentage
1	Joy	16.7
2	Trust	66.7
3	Fear	00.0
4	Surprise	00.0
5	Sadness	00.0
6	Disgust	00.0
7	Anger	00.0
8	Anticipation	16.7

The summary report, aggregating emotional data from Sample1.docx and Sample2.docx, provides a more balanced overview of the emotional landscape across both documents. Anger remains the most prominent emotion at 35.0%, followed by Surprise and Trust, both at 25.0%. This shows a blend of negative emotional intensity and elements of both unexpected and positive expression. The remaining emotions, Anticipation, Joy, and Sadness are equally represented at 5.0% each, suggesting a minor but diverse emotional presence (Table 3).

Table 3: Summary of Emotional Analysis Report.

Sl.no	Emotions List	Percentage
1	Joy	05.0
2	Trust	25.0
3	Fear	00.0
4	Surprise	25.0
5	Sadness	05.0
6	Disgust	00.0
7	Anger	35.0
8	Anticipation	05.0

This combined summary reflects a moderately diverse emotional distribution with a leaning towards strong emotional expressions like anger and surprise, tempered by a consistent presence of trust. The overall interpretation suggests mixed sentiments, likely influenced by contrasting tones between the two documents one being largely negative (Sample1) and the other more positive (Sample2).

3.1. Application Validation and Performance Evaluation

In the future, it will be desirable to conduct software validation as well as to measure the emotion-classification performance to enhance the validity of the proposed application. The software should be evaluated for correct operation of all the core functions, such as user authentication, .docx file upload, text extraction, word tokenization, loading of a lexicon, emotion-word matching, calculating the frequencies, converting to percentages, generating a local and cumulative summary and generating graphical visuals. Reflective reports of varying length, style and emotional content should also be used for application testing to guarantee stability, consistency and usability in varying application input.

In addition to functional testing, the analytical performance of the emotion detection module should be evaluated against a human-annotated reference standard. A representative sample of anonymized reflective reports may be independently reviewed by trained educators or domain experts and coded according to the eight NRC emotion categories: joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. The application-generated results can then be compared with the expert-coded results to determine the level of agreement and classification reliability.

The performance of the system should be reported using standard evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Accuracy would indicate the overall proportion of correctly identified emotion categories, while precision would show the extent to which detected emotions are relevant. Recall would indicate the system's ability to identify all relevant emotional expressions, and the F1-score would provide a balanced measure of precision and recall. A confusion matrix would further help identify which emotions are frequently misclassified, particularly in cases where emotional categories overlap or appear in low frequency.

Inter-rater reliability among human annotators should also be considered before using the annotated data as a reference standard. Measures such as Cohen's kappa or Fleiss' kappa may be used to determine the consistency of expert judgments. In addition, system-level performance indicators, including processing time, file upload success rate, application responsiveness, and stability across Android devices, should be assessed to determine whether the application is suitable for practical educational deployment.

3.2. Accuracy Measures and Potential Classification Limitations

The present application adopts a lexicon-based emotion analysis approach using the NRC Word-Emotion Association Lexicon. This method is suitable for an initial mobile-based implementation because it is transparent, computationally efficient, and easy to interpret. Each detected emotional word can be traced to a predefined lexicon entry, allowing educators to understand how the application generates its results.

However, the accuracy of the system is dependent on direct or close matches between words in the reflective reports and the predefined lexicon. This creates several classification limitations. First, the method treats words largely as independent units and may not fully capture sentence-level or paragraph-level meaning. As a result, contextual features such as negation, sarcasm, irony, indirect expression, and emotional ambiguity may not be accurately interpreted. For example, a sentence such as "I was not angry" may still be associated with anger if negation is not adequately handled.

Second, reflective reports often contain complex and nuanced emotional expressions. Students may express empathy, discomfort, uncertainty, concern, or moral reflection without using explicit emotion-related words. Such expressions may be under-detected by a purely lexicon-based system. Conversely, the system may over-detect an emotion when an emotion-related word is used descriptively rather than personally, such as when a student describes another person's anger or fear.

Third, some words may carry different emotional meanings depending on cultural, educational, or situational context. Since the NRC lexicon provides general word-emotion associations, it may not fully reflect the specific language patterns used by undergraduate medical students in reflective writing. This may lead to false positives, false negatives, or reduced sensitivity for subtle emotional states.

Therefore, the findings generated by the application should be interpreted as indicative emotional trends rather than definitive psychological or diagnostic conclusions. The tool is best positioned as a supportive learning analytics aid for educators, not as a replacement for expert interpretation of reflective writing

4. CONCLUSION AND FUTURE DEVELOPMENT

This study demonstrates the development of a mobile application for detecting and visualizing emotions in undergraduate medical students' reflective reports. The application integrates Android-based mobile development, Word document processing, lexicon-based emotion analysis, and visual output generation through bar charts. By presenting the emotional distribution of reflective reports in percentage form, the system offers educators a structured and accessible way to examine students' emotional engagement with learning experiences.

The initial results show that the application can differentiate emotional patterns across sample reflective reports. One sample document showed a higher proportion of anger and surprise, suggesting a more negative or emotionally reactive tone, whereas another sample showed stronger trust, joy, and anticipation, indicating a more positive and constructive emotional orientation. These outputs suggest that automated emotion analysis may help educators identify broad emotional trends in students' reflections and support more informed feedback on reflective practice.

However, the current study should be interpreted as an initial developmental and feasibility study rather than a complete validation study. The analysis was demonstrated using a limited number of sample documents, and the outputs were not yet compared with expert human annotations. Therefore, the present findings confirm the functional capability of the application, but they do not yet establish its full classification accuracy, reliability, or generalizability. Future studies should include a larger corpus of anonymized reflective reports and compare the application results with independently coded human judgments.

A key limitation of the current system is its reliance on lexicon-based emotion analysis. While lexicon-based methods are transparent, efficient, and suitable for mobile implementation, they are limited in their ability to interpret context. Unlike machine-learning approaches, lexicon-based methods do not learn from annotated examples and may not fully capture sentence structure, semantic relationships, implicit emotions, emotional intensity, sarcasm, negation, or mixed emotional states. Machine-learning and deep-learning approaches, including transformer-based natural language processing models, may provide improved accuracy by learning contextual patterns from large, annotated datasets. However, these approaches require sufficient training data, expert annotation, computational resources, and careful validation to avoid bias and overfitting.

Future development should therefore consider a hybrid analytical model that combines the transparency of lexicon-based analysis with the contextual strength of machine-learning methods. Enhancements may include negation handling, lemmatization, phrase-level analysis, sentence-level emotion classification, emotional intensity scoring, and comparison with supervised machine-learning classifiers. The application could also be expanded to include educator dashboards, longitudinal tracking of student emotional development, downloadable reports, and integration with learning management systems.

The educational applications of the system may extend beyond undergraduate medical education. Reflective writing is widely used in nursing, pharmacy, dentistry, psychology, counselling, teacher education, and other professional programmes. With further validation, the application could support reflective practice assessment, emotional intelligence development, student wellbeing monitoring, and curriculum evaluation. Importantly, any future use of the system should maintain strict ethical safeguards, including anonymization, secure data handling, informed consent, and clear communication that the tool is intended to support not replace educator judgment.

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Acknowledgements: We would like to acknowledge the use of the open-source NRC lexicon database created by Dr. Saif M. Mohammad, Dr. Peter Turney at the National Research Council Canada (https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm).