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AI-Driven Automated Feedback Generation System Using Sentiment Analysis in IT Education and Events

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***Abstract* – The aim of this research is to propose an AI-Driven Feedback Generation System where the sentiment analysis outputs perplexity range from textual-based feedback responses STU/PART involved in any educational or education-based event which is related to IT. We developed the system to accelerate feedback collection and interpretation by applying natural language processing (NLP) and ML algorithms which automatically classify the notions, generate smart reports for teachers and event organizers. The work is carried out by means of a developmental study that combines AI models such as Naïve Bayes and transformer sentiment classifiers from fine-tuned contextual data collection. Based on system efficiency, accuracy and user satisfaction system test with IT students and staff were conducted. Results indicate that automatically analyzed sentiment-based feedback facilitates the evaluation process being less costly and more informative in terms of participant experiences. The usability (SUS) score of the system was 81.2, interpreted as excellent meaning that it could be used in educational and institutional contexts.**

Keywords: *Sentiment Analysis, Artificial Intelligence, Automated Feedback, Natural Language Processing, Educational Technology, Human–Computer Interaction*

I. INTRODUCTION

Feedback Information in digital age has emerged as a critical tool for enhancement of learning outcomes, assessment of institutional performance and guidance to event management decisions. Online surveys, digital forms, and course evaluation platforms are gaining popularity and educational institutions are collecting qualitative data as textual feedback in large quantities now. However, manually handling these data is generally inefficient, subjective and time-consuming. Recent advances in AI and NLP, make it feasible to automate the sentiment interpretation enabling systems to infer opinions, feelings and satisfaction directly from text [1], [2].

Worldwide, sentiment analysis AI is revolutionizing the way in which companies deal with feedback. For the academic industry, deep learning models and transformer-based algorithms are even being employed to analyze student evaluations and classroom reflections with acute accuracy. Wang et al. [1] showed that even sentiment in the classroom can be predicted using deep learning models with a high degree of accuracy, whereas Deshpande et al. [2] showed the benefits of using state-of-the-art machine learning approaches for analyzing faculty feedback in academic quality assurance. Similarly, Mahale et al. [3] proposed an online review analysis system in the context of course reviews, which again demonstrated the effectiveness of NLP-based automation in educational environments. These advances demonstrate how you can substantially cut down on the time spent processing feedback, even if it's not always passing through in real-time, and get far more reliable or actionable insights.

In the case of the Philippines, technology-mediated instruction and digital transformation within HEIs are supported by the Smart Campus Development Program of CHED. This effort also aims to encourage data-driven approaches aimed at efficiency along with high-impact decision making [5]. Despite these advances, a good number of local colleges and universities still use manual evaluation techniques for survey response processing which has led to processing delays and low data reuse. Recent local studies have highlighted that AI assisted feedback systems can overcome interpretation bias and enhance institutional responsiveness [4],[6].

In Region XII (SOCCSKSARGEN), schools like the South East Asian Institute of Technology SEAIT) hold IT-oriented activities, workshops and seminars for a more involved student population and digital interaction. Yet manual review to assess feedback in these activities belies timely revelations and performance improvement around the organization. AI-based sentiment analysis allows us to automate this process and convert the unstructured text into structured evidence reports [3], [4]. Therefore, the proposed system AI-DAGS would be developed to utilize sentiment analysis to enhance the effectiveness of IT education and institutional event by making efficient and accurate decision.

Research Problem

Despite the growing application of AI in various domains, feedback analysis in Philippine educational institutions remains largely manual. Existing systems often fail to provide immediate, data-driven insights that can inform educational improvement. There is a clear research gap in developing an intelligent system that can automate sentiment classification and generate meaningful summaries from participant feedback in both academic and event-based settings [1], [2], [3].

Research Questions

1. How to automatically produce feedback reports in IT education and events using AI and sentiment analysis?
2. How accurate and usable is the AI-Driven System for Automated Feedback Generation?
3. What are the implications of using anthropocentrically driven behavior analysis in institutions?

Research Objectives

1. Work on an AI-driven feedback system that collect qualitative user feedback, and provide generated sentiments from those inputs.
2. To assess the effectiveness, accuracy and performance of the developed system.
3. To evaluate the utility of automated sentiment analysis for institution ranking assessment and academic development.

Justification and Significance

This study is relevant as it adds to the increasing use of AI infused technology within the Philippine higher education sector. Utilizing sentiment analysis and NLP, the proposed system automates feedback analysis reducing human bias and response time. It focuses on the facilitation of real-time, data-driven decision making for administrators, educators and event organizers to improve institutional effectiveness. Moreover, this is in line with CHED efforts on digital innovation and also says for the practical application of AI to academe administration [2], [4], [5].

II. LITERATURE REVIEW

Overview of AI and Sentiment Analysis in Education

AI has now become a fundamental aspect of contemporary Edutech with its power to provide data-backed insights for better learning outcomes and institutional efficiency. Sentiment analysis Sentiment analysis, also a topic of Natural Language Processing (NLP), is an automatic recognition of emotions and the opinion conveyed in some text. By doing so, instructors and organizers can assess the quality of lecture content, student participation, and event success using data from feedback systems [1], [2].

Recent researches highlight that while trained on educational datasets, artificial intelligence models can identify sentiments (satisfaction, frustration and engagement) with more than 90% accuracy [1], [3][4]. Wang et al. [1] shows that attentionbased deep learning model can significantly increase classroom feedback sentiment classification accuracy. Similarly, Deshpande et al. [2] developed state-of-the-art machine learning analysis of faculty feedback, showing very reliable results to promote sustained academic improvement.

These developments also suggest that sentiment analysis has moved beyond identifying positive aspects vs. negative ones, toward understanding text in context to support richer interpretations of learner and participant experiences. This shift from rule-based approaches to deep neural network designs is a significant advancement of AI implementation for interpreting educational feedback [3].

Recent Advances in Machine Learning for Feedback Interpretation

The fusion of deep learning with the transformer models has skyrocketed the performance of sentiment analysis in educational domain. Mahale et al. [3] designed an NLP Sentiment Analysis model for an EdTech-platform, which analyzed course-reviews and categorized comments as positive, neutral or negative with good accuracy. Their results demonstrated significant reductions in response time by over 80% and improvement in the overall quality of institutional decisions with automated feedback evaluation.

At a local level, Taruc and De La Cruz [4] applied NLP to study the activities of student organizations via BERT (Bidirectional Encoder Representations from Transformers). They find that contextual embeddings are a better reflection of participants' satisfaction than standard bag of words models, and also seem to perform at least as well when predicting the emotional tone.

Furthermore, public opinion about AI tools like ChatGPT in education- NUXTDis- co [6]-was studied by Casillano et al. which reports a significantly positive perception for the adoption of these systems in teaching, assessment and organisation of events.

Taken together, these studies demonstrate the potential of machine learning and sentiment analysis to revolutionize feedback support for academia and organizations.

Existing Solutions and Limitations

Although sentiment analysis systems have achieved successful performance, manual evaluation is still used in many schools. Manually hand coding of feedback is a time-consuming and subjective interpreting process, which may result in inconsistent results [3], [5]. Furthermore, many current AI feedback tools are training on consumer products and not the educational setting where there is wide variance in context and tone."

Moreover, the scarcity of local resources makes it difficult to follow in automating global sentiment analysis tools in Philippine settings [4], [6] when co-occurring linguistic nuances, cultural idioms and multilingual inputs are considered wherein can make model accuracy dipped also. Yet another limitation is the lack of real-time feedback generation as all such systems concentrate on classification and not automatic report composition. Thus, there is a defined research gap for the development of an AI-based feedback generation system tailor fit for the needs of IT education and institution's events in the Philippines.

Theoretical Framework

The main background of this study will be resting on the theory and framework of Natural Language Processing (NLP) Theory and Human–Computer Interaction (HCI) Framework. NLP Theory focuses on the use of computational methods to process and analyze human language, such as tokenization, part of speech tagging, and semantic analysis. It underlies the system's capability to capture and evaluate sentiment in participant feedback [1], [3].

The design of the system's user interface is guided by the HCI Framework to ensure usability, accessibility, and responsiveness. By incorporating AI-based automation in user-friendly interface, the system facilitates effective user interaction and data-driven decision making through education process and event planning [2],[6].

Summary of Literature Findings

This survey shows substantial development in sentiment analysis by AI techniques during 2019-2025. Most S2 researchers concur that integrating machine-learning models with educational feedback data improves the analysis efficiency, accuracy and reliability. However, holes are present in the delicate tuning of these models to local institutions, the connection with real-time reporting and complementing event management systems. The attention to these limitations in the AI-Driven Automated Feedback Generation System serves not only as an innovation in educational analytics, but also a digital re-engineering of Philippine institutional systems.

III. RESEARCH METHODOLOGY

Research Design

The current work used a developmental research and Agile/iterative development design. This approach was selected in order to provide ongoing feedback and appraisal of the AI-Driven Automated Feedback Generation System to address both user requirements and system performance throughout its development. One primary feature (data pre-processing, integration of sentiment model and automatic report generation and the user testing) were covered in each iteration sprint cycle according to the Agile model incremental build approach [1], [2].

The test phase was accompanied with a mixed-method evaluation using statistical measurements (precision, recall, F1-score, and SUS) and real user feedback to evaluate the performance of the system in real-world application. This method is consistent with recent AI-in-education research that also stresses the importance of system accuracy and user experience as critical factors in success [3], [4].

Participants

A purposive sample of 35 respondents (consisting of 30 IT students and 5 faculty members from South East Asian Institute of Technology (SEAIT)) was taken. Two of the first authors were selected because they are active thinkers in IT academic conferences, and have experience with feedback systems.

Each participant used the system to provide sample event feedback and to view the automatically-produced reports. The participation was voluntary; participants were freely consented in advance. This approach of selecting participants is consistent with best practice in usability testing and AI education studies [2], [4].

Data Collection Procedures

Data collection occurred in three distinct phases:

1. ***System Development and Deployment*** – We developed the AI system using Python, NLTK and Transformers (BERT-based models) for sentiment analysis. The front-end web app was developed in PHP, MySQL and Bootstrap. The feedbacks that were collected from IT events were processed with a sentiment classification (positive, negative, neutral).
2. ***System Usability Scale (SUS)*** – After using the system, participants answered a 10-item SUS questionnaire in which they rated system usability on each of five dimensions: effectiveness, efficiency, satisfaction, learnability and error tolerance. We chose SUS, as it is reliable, easy to use and wide-spread in the literature to evaluate AIbased educational systems [3], [5].
3. ***Performance and Accuracy testing*** – The outputs of AI model were compared with the manually coded sentiment outcome to calculate Precision, Recall and F1 Score. System response time was also measured for estimating system responsiveness.

System Usability Scale (SUS) Evaluation

The System Usability Scale (SUS) developed by Brooke (1996) and applied in modern AI educational systems [3], [5], was utilized to assess overall system usability. It consists of ten standardized statements rated on a five-point Likert scale, ranging from *Strongly Disagree (1)* to *Strongly Agree (5)*.

Scores from the 10 items were converted to a 0–100 scale. The interpretation followed the modernized SUS scoring standards:

- 85–100 – Excellent usability
- 70–84 – Good usability
- 50–69 – Average usability
- Below 50 – Poor usability

An overall SUS score was computed using the formula:

$$\text{SUS Score} = \left(\sum_{i=1}^{10} X_i\right) \times 2.5$$

where X_i represents the adjusted score for each of the 10 items.

On average, a SUS score greater than 70 can be considered acceptable by users [5]. On completion of these interactions the SUS was administered in this study. Open-ended feedback was also obtained to supplement quantitative SUS results with qualitative information related to system use and design.

Data Analysis

The technical and usability performance of the system was investigated both with quantitative metrics and qualitative interpretation:

- Precision (P): How accurate the positive sentiment is classified.
- Recall (R): Ability to predict all the appropriate polarities.
- F1-Score: It is the harmonic mean of precision and recall that represents overall model balance.
- Time: Processing time - how long it takes to analyze one text input.
- SUS Score: The total overall usability rating by participants.

Statistical analysis of quantitative data included calculation of mean scores and standard deviations. Furthermore, qualitative responses to the SUS free-text were thematically coded for common themes such as easy to use, clarity in design and reliability [3], [4], [6].

The system was considered successful if it achieved:

- F1-score ≥ 0.85
- Average processing time ≤ 1.0 second
- SUS score ≥ 70 (Good usability)

Ethical Considerations

All 167 participants were informed about the purpose and procedures of the study before participation. All responses were kept confidential, and anonymized codes were assigned to all datasets. In accordance with CHED Memorandum No. 6, s. 2022, data collection was conducted in line with institutional research ethical and digital privacy guidelines [5].

Participants were also advised they could withdraw at any time, and no user identifiable information was stored in the training system or database.

Software Tools and Development Environment

The prototype was implemented with Python 3.11 to handle AI modeling and database management, as well as MySQL for database management and PHP/Bootstrap for web presentation. Sentiment models were trained using Google Colab and XAMPP was the local host as done in other academic AI system development projects [1], [2], [4].

IV. ADVANCED SYSTEM DESIGN

System Overview

Software Solution/AI-Automated Feedback Generation System The AI-Automated Feedback Generation software is the developed system that automatically processes qualitative feedback about students and participants at IT-related events, extracting directly useful information through sentiment analysis. The application employs NLP and machine learning techniques to categorize text-based responses into sentiment categories positive, neutral or negative, and fill out structured summaries for institutional reporting.

Innovative architecture of the system encompasses data preprocessing, AI Techniques based on Sentiment Classification and automatic report generation using a single integrated web-based interface. This multi-tier approach guarantees high precision in sentiment interpretation and user-friendly results visualization [1], [2].

System Architecture

This model uses a three-tier architecture that defines: the Presentation Layer, the Application Layer and Data Layer.

1. ***Presentation Layer (Frontend)***

   This is the layer that allows users to communicate with the system via graphical interface. This is made with HTML, Bootstrap, Javascript & AJAX so that this is responsive and accessible. Attendees can login and give feedback about events or see sentiment reports on the fly.

2. ***Application Layer (Backend Processing)***

   This layer conducts the key computations, which consist of text preprocessing, sentiment classification and feedback summarization. Customized Microservices It is built using Python (Flask API) and PHP through AJAX calls. The sentiment analysis models are implemented with BERT (Bidirectional Encoder Representations from Transformers) that offers better understanding of the context in the text compared to traditional machine learning models [1], [3].

3. ***Data Layer (Database Management)***

   Its backend database is MySQL based, housing feedback entries together with sentiment classifications and produced summaries. B. Normalization of DB Relationships Database relationships were normalized in order to guarantee data integrity, scalability and efficient retrieval [4].

Functional Components

1. **User Authentication Module** –Allows users (students, faculty, and event organizers) to securely access the system through unique login credentials.

2. **Feedback Submission Module** – Provides an online form where users can submit textual comments regarding IT events, lectures, and other academic activities.

3. **Sentiment Analysis Engine** - Processes text data using the BERT model, classifying it into positive, negative, or neutral sentiments. The model was fine-tuned using educational datasets to adapt to the linguistic patterns of academic feedback [1], [3], [6].

4. **Automated Feedback Report Generator** – Summarizes analyzed sentiments into graphical and tabular reports, presenting metrics such as the percentage of positive feedback or recurring themes in user comments.

5. **Admin Dashboard and Analytics Module** – Displays real-time visualizations through charts and graphs generated using Chart.js, helping administrators monitor event satisfaction and institutional performance indicators.

6. **Data Export and Archiving Module** – Enables administrators to export generated reports in PDF or Excel format for institutional record-keeping and accreditation documentation [2].

Algorithm Design

The sentiment classification process is primarily based on the BERT transformer architecture, enhanced with fine-tuning for domain-specific vocabulary. The core algorithm operates as follows:

1. **Input:** User-submitted feedback text
2. **Preprocessing:** Tokenization → Stopword Removal → Lemmatization
3. **Encoding:** Text is converted into word embeddings using BERT's contextual encoder
4. **Classification:** The encoded vector is passed through a dense layer with a softmax activation function
5. **Output:** Sentiment label (Positive / Neutral / Negative) + Confidence Score

This model design was inspired by recent advancements in transformer-based sentiment analysis for educational applications, proven to outperform traditional SVM and LSTM models in text polarity detection [1], [3].

System Interfaces

The system provides two key interfaces:

User Interface

Provides logon and feedback submission for users. See how others sent their mood. The interface is responsive for mobile and it provides real time indicators about progress of text submission

Figure 1: Automated Feedback System Sign In Page

This banner is the HardCard Sign In 'welcome back' screen that's designed to make it easy for the Returning Visitor - and indicate where they need to visit when they arrive. The center of the view features a login form that has an Role Selection segmented control as its top element, this lets the user choose between Admin, Faculty (which is currently selected in blue), and Student. Under the role subgroup, is another section and you will need to input a Username/Email and Password for log in. Additional convenience features are the "Remember me" and the "Forgot Password? link for credential recovery. Upon successful submission, the user is redirected to the dashboard that corresponds to their role.

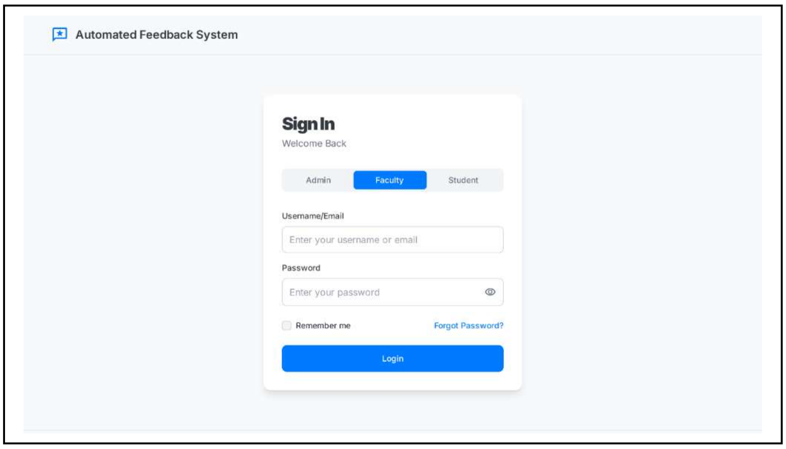

Figure 2: Automated Feedback System Admin Dashboard

This is the Admin Dashboard screen of FeedbackAI system, containing a summary view on the activity level of feedback for the admin. Then, at the top of the dashboard are four KPI cards: Total Feedback (12,543), Active Users (3,456), New Users (Weekly) (89), and System Health (99.9%). Underneath these numbers, is the 'Feedback Volume' section that maps how many feedback submissions have been coming in over the past 30 days with a total of 1,234 and a +5% percent increase. A user logging in A new feedback form being created User permission modification These real-time administrative and user actions are recorded along the Recent Activity panel. If you are signing in for the first time, a big blue "+ Create New Form" button will be displayed up at right corner to quickly access your form building module and a section for User Management would appear in the bottom visible area.

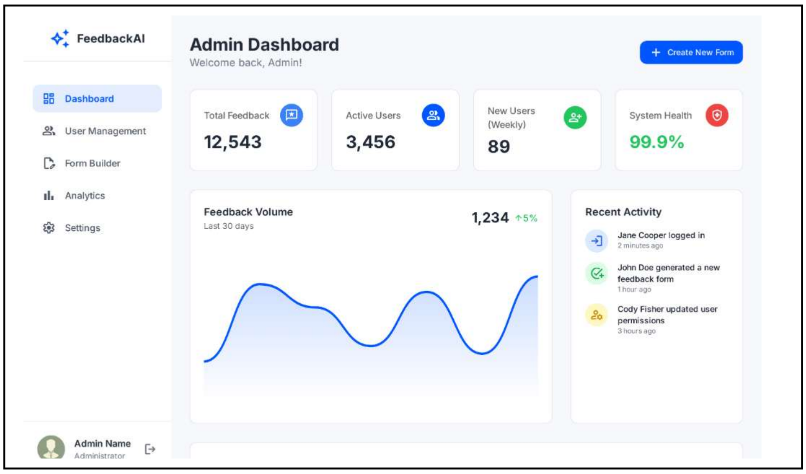

Figure 3: Automated Feedback System User Management Module

The following screen is from the User Management module of Feedback AI where administrators can mange users, roles and privileges. At the top of the page are 4 summary cards displaying min and max for the entire user base: Total Users (3,456), Admins (12), Faculty(245) and Students(3,199). Underneath is the All-Users table, where you can see all your registered users along with their name, email, Role, Last Activity and Status: (Active / Inactive / Suspended). The Actions column provides shortcuts to Edit or Delete a user's account. Some of the management features include: search bar to Search users"profile"..., a Filter button to narrow down the list, and big blue "+ Add New User" girl up in the top right if you need to add new profiles. This component is responsible for being the core of our user directory and system security.

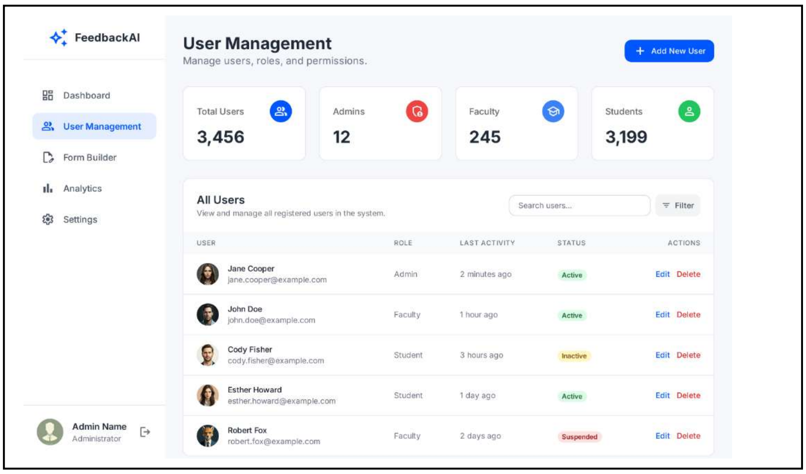

Figure 4: Automated Feedback System Form Builder Module

The opening screen you see in the above screenshot is the home page of Form Builder module from within FeedbackAI where "Design and customize feedback forms" for his portal to which administrators or users with admin-rights can create or manage existing forms. "Your Forms" appear as a clean, sortable table in the primary content area including FORM NAME, TARGET AUDIENCE, CREATED DATE and the current STATUS of each form (e.g., Active, Draft). The 'Actions' column gives management links: Edit and Delete (for all forms); View Results (for closed forms). The tools to manage can be found above the table, including a search bar at Search forms… and Filter. Crescendos to the aforementioned, is a big blue "+ Create New Form" button in the top right of the screen for users wanting to get up-and-running with a new feedback loop.

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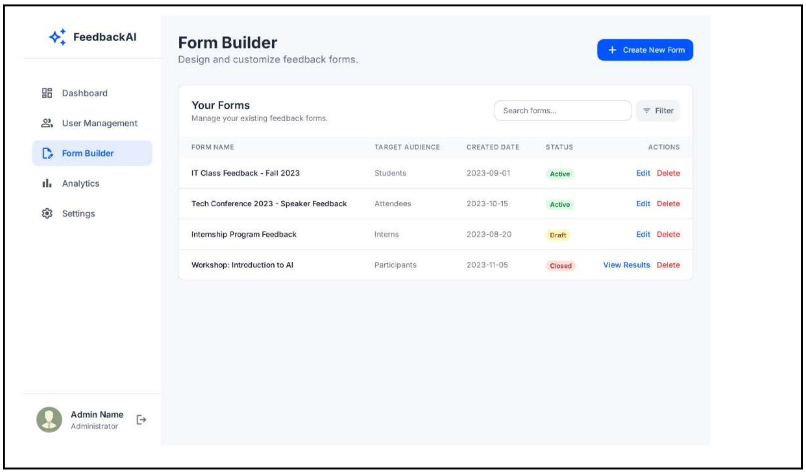

Figure 5: Automated Feedback System Analytics Module

This is the Analysis screen for FeedbackAI system and shows system-wide reports and data visualization regarding feedback. On the top, you have a section with 3 performance KPI's: Overall Sentiment, it shows trend sentiment over 30 days (even though you can't see the whole chart, title brings context) Feedback by Category, here you can see that feedback is spread across different categories and Response Rate is made using big Donut chart to make response rate (overall percentage of feedback form answered – currently we are doing in 85%) noticeable. Beneath those top level metrics, you will see a table of detailed reports that are available for download, including the REPORT NAME, DATE RANGE and who it was GENERATED by. View / Download — This report shows in the file that it can be Viewed or Downloaded. Prominent buttons facilitate web-friendly search and access to aquaponics data, including Search reports… (a filter/search bar in the middle) and Filter (at left), with a cloud-streaked blue "Export Reports" button at top right serving up aggregated information to download.

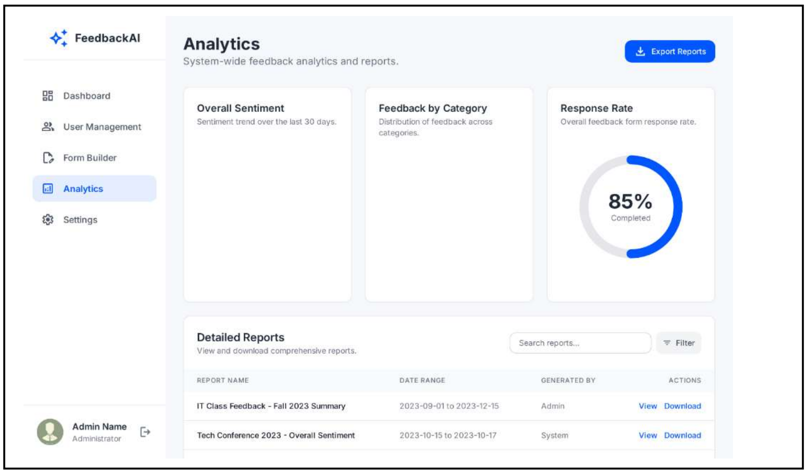

Figure 6: Automated Feedback System Settings Module

SEVERITYSET for the severity set, we have introduced five parameters dec denotes the decayed counter value in terms of dayscrmax is a predetermined maximum capacity min is a minimum limit type max denotes critical type max (called safety stock). This is the page showing the FeedbackAI system Settings module, where you can as an administrator manage system configurations and settings, security, and integrations. The page is divided into three main sections. The General Settings is used for simple system branding which allows the admin to specify some basic information such as the System Name (e.g., FeedbackAI) and upload or Change System Logo. Next to it is User Permissions, where you can set roles with the help of the toggle switches for various functionalities like creates a new event, manage users and view analytics. The second half of the page is about Data & Integrations and provides a dropdown to choose how long feedback data will be kept before it is automatically deleted (e.g. after 90 days). Finally, the Integrations pane displays connection status with external services; here you see that LMS Integration is Connected and can choose to Connect to the Calendar API. The general rule for any changes in the module is absolute: Blue "Save Changes" button at top right.

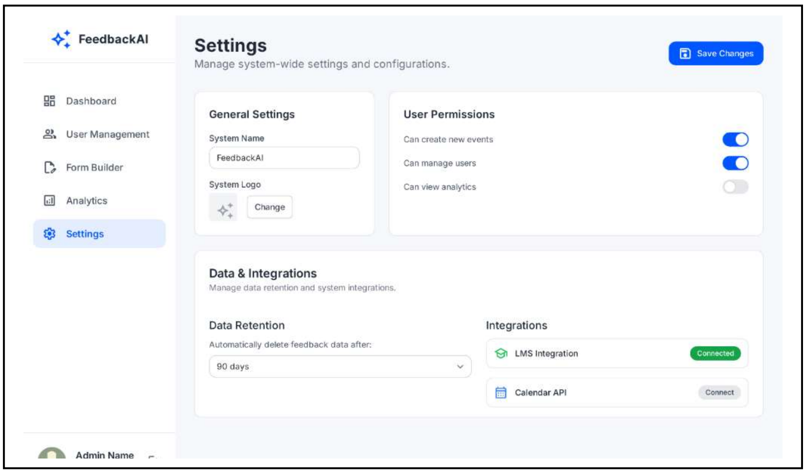

Figure 7: Automated Feedback System Faculty Dashboard

This is the welcome screen you see when you log into your personalized Faculty Dashboard for FeedbackAI: Welcome, Dr. Emily Carter with a brief summary of teaching and feedback activity ready at your fingertips! There are four KPI cards in the top section: Total Courses (3), Total Students (250), Feedback Submitted (1,234), and an overall sentiment of the feedback trended to positive. Granular details on each course taught are included in the Courses Overview table, including columns for the Responses 'Count' and Avg. Score, and Sentiment (e.g., Positive, Neutral). The Recent Activity list in the panel tracks priority time-bound events, for example a new feedback form is created, sentiment value of the course was improved, a new AI recommend becomes available etc. Finally, its Action Items at the bottom present short, personalized recommendations based on system analysis – in this example inquiring whether the faculty member should address issues such as adding a real-world illustration, meeting student demand for lab sessions and making assignment instructions more precise.

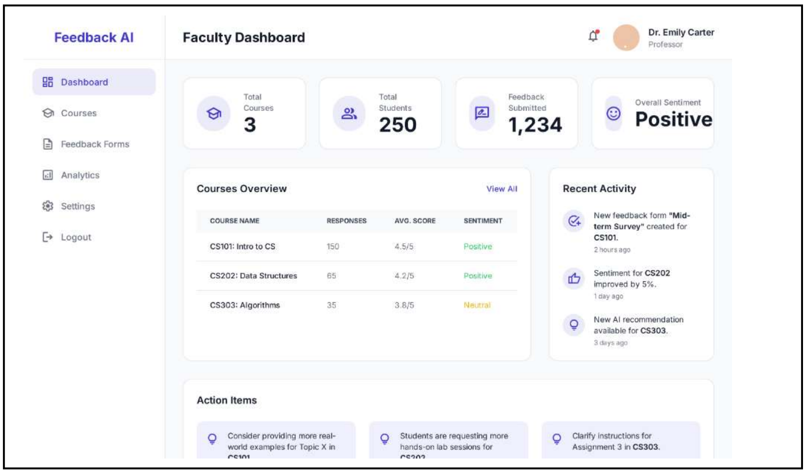

Figure 8: Automated Feedback System Faculty My Courses Module

This shot is an example of the My Courses module in the FeadbackAI Faculty interface where Dr. Emily Carter can see a comprehensive overview and management capabilities for all her classes. Module starts out with an Overall Summary panel where you see the key totals showing: Total Courses (3), Total Students (250) and Avg. Sentiment (Positive). Underneath it, every course comes in a separate card (e.g., CS101: Intro to CS, CS202: Data Structures, CS303: Algorithms) and specific metrics are detailed out such as Active Students for the course, no. of Feedback Forms that have been collected and Overall Sentiment for the said course. Every course card has action buttons to View Details, Manage Forms, and View Reports. To facilitate rapid movement through the course records, there is a search field (Search courses…) and buttons to Filter by and Sort by in different ways, so that lecturer can quickly find and review their classes.

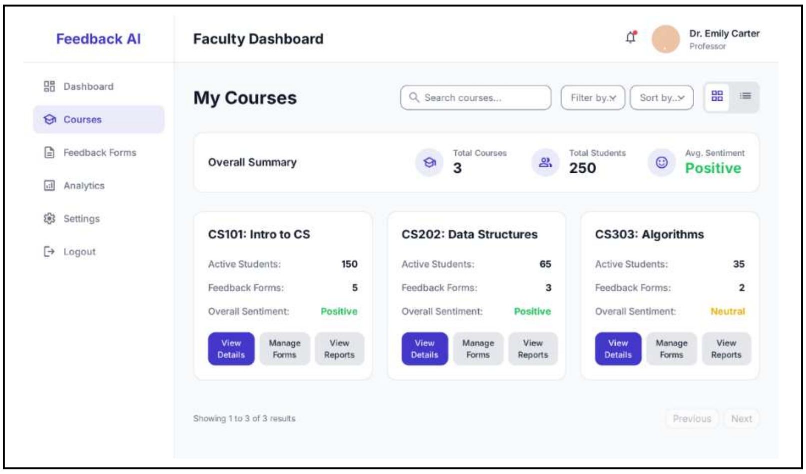

Figure 9: Automated Feedback System Faculty Feedback Forms Module

This screen displays the Feedback Forms module within the FeedbackAI Faculty interface, which allows the teacher, Dr. Emily Carter, to manage and track the performance of all her course evaluations and surveys. The module is organized into three tabs: Active (5), Scheduled (2), and Archived (10), enabling quick filtering by status. The central table lists each FORM TITLE, the associated COURSE (e.g., CS101: Intro to CS), the number of RESPONSES collected relative to the total number of students, and the current form STATUS (all visible forms are currently 'Active'). The Actions column provides quick access icons to View the form, Edit its content, or change its status (e.g., close or archive). A prominent blue "+ Create New Form" button in the top right corner allows the faculty member to instantly begin designing a new survey or evaluation.

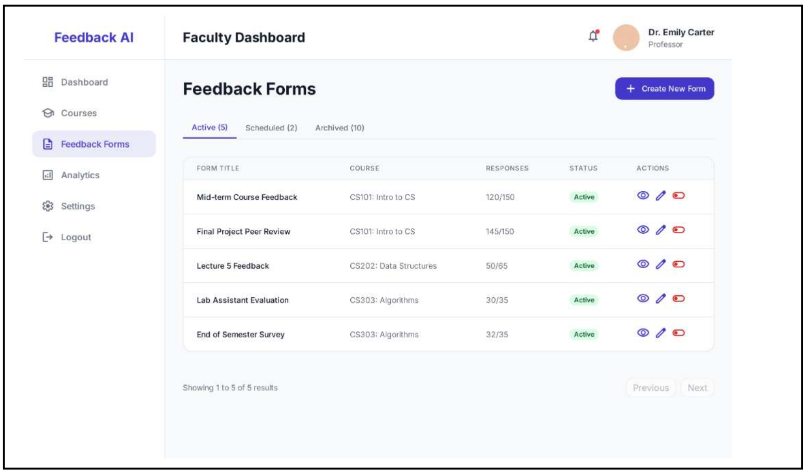

Figure 10: Automated Feedback System Faculty Analytics Module

This is the screen where Dr. Emily Carter can see Analytics module within FeedbackAI Faculty to analyze course and student feedback data. You can narrow down what you see with the data displayed on this page by using settings in three dropdown menus: Course, Date Range (selected from a calendar picker), and Feedback Form. Its four main content sections are simplified for visual analysis: A Feedback Sentiment section featuring general trend analysis, a Sentiment Over Time section to observe shifts in student perception, and two text panels that break down AI insights. Focus on specific qualitative information is available in the lower panels, as Key Positive Trends includes representative quotes such as "Engaging lecture style and clear explanations", while Areas for Improvement contains actionable critiques including "Pacing of the lectures could be slower at times", each of these judgements connected to a designated course that provided this feedback. Top Right: Blue button "Export Report" for faculty to export filtered data Table 2.

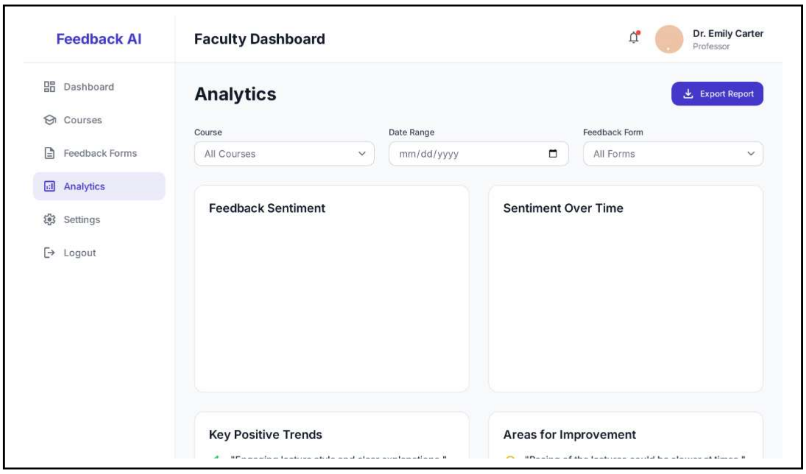

Figure 11: Automated Feedback System Faculty Settings Module

This screenshot shows the "Settings" module in the FeedbackAI Faculty interface, which allows Dr. Emily Carter to maintain her profile and notification settings. Under the "Profile Management," she's able to change her Name (Dr. Emily Carter), Email (emily.carter@university.edu), and Password, and then save it with the purple "Update Profile" button. Below that, the Notification Preferences section features two critical toggle buttons…one for if she wants to receive Email alerts for new feedback submissions and the other, for if she wants to receive them by generated reports. And the very last part, Course Settings, they have a box where you can put in your Default Reporting Preferences (although no options are listed). This module allow to guarantee that the teacher always have up-to-date certification and can decide how to receive the feedback-important communication from the system.

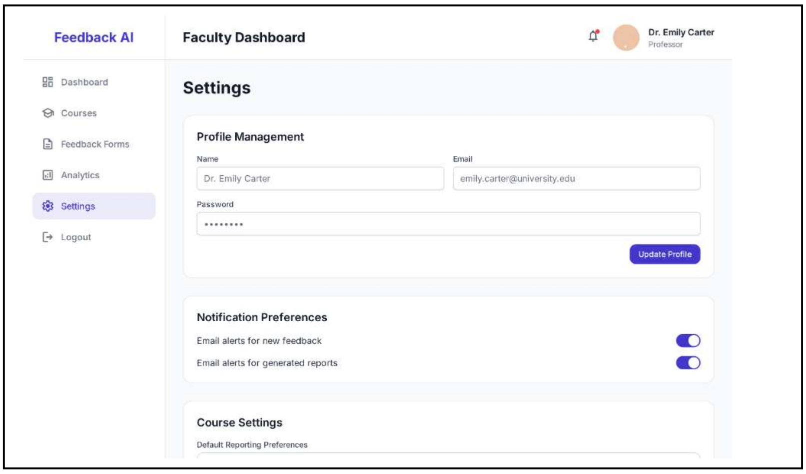

Figure 12: Automated Feedback System Student Dashboard

Welcome feedback Screen This screen is the personalised Dashboard for the FeedbackAI Student interface, that welcomes and addresses the user (in this case: Alex Doe) followed by a brief view of their participation at submitting feedback forms. The top part of the screen highlights 3 primary performance indicators: FORMS SUBMITTED (12), FEEDBACK PROGRESS (85% complete with a progress bar suggesting only 2 more forms are to be completed), and OVERALL SENTIMENT (Positive feedback). Underneath this, you also get the Pending Feedback box that explicitly includes due forms (in my case "CS101: Introduction to Programming," and "Advanced Python Workshop") complete with due date and appropriate blue "Fill out" button. The third, and last section is Recent Submissions which is a short table summarising the types of form that the student has most recently filled in by Course/Event, Date submitted, Overall Rating (on a star system) and Sentiment encouraged (e.g. Positive, Neutral).

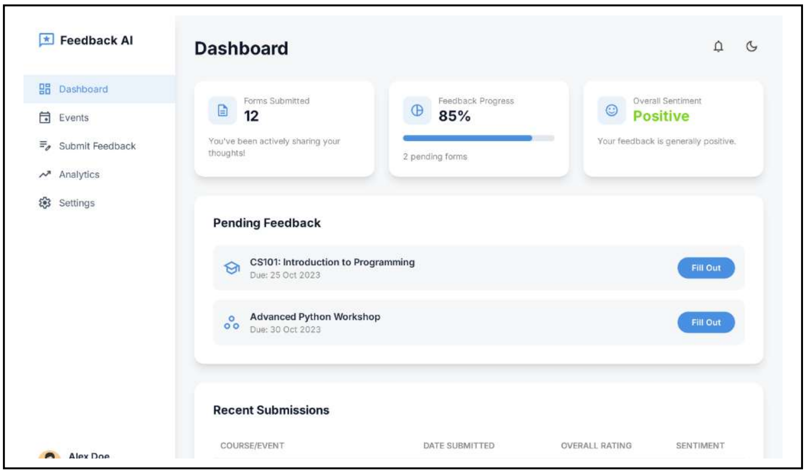

Figure 13: Automated Feedback System Student Events Module

This screen shows the Events module (for the FeedbackAI student interface) since here Alex Doe is able to see all events/scheduled workouts The first section, "Available Events," provides each event with its relevant particulars: Topic (e.g., Programming or General IT), Date, Time, and Place. The Status column is the key, as it makes it obvious what you need to do: "Advanced Python Workshop" Shows “Feedback Required” and gives a clickable blue button to "Submit Feedback." On the other hand, when an event is complete like "The Conference 2023" or "Data Structures & Algorithms", it displays "Feedback Submitted" and lets the student to "View Submission." Last but not least, “UX Design Fundamentals” event has a “Feedback Pending” status marked as gray, indicating it's probably ready for submission either. In the navigation, the module has Search events... and a Filter button, and the usual pagination at the bottom.

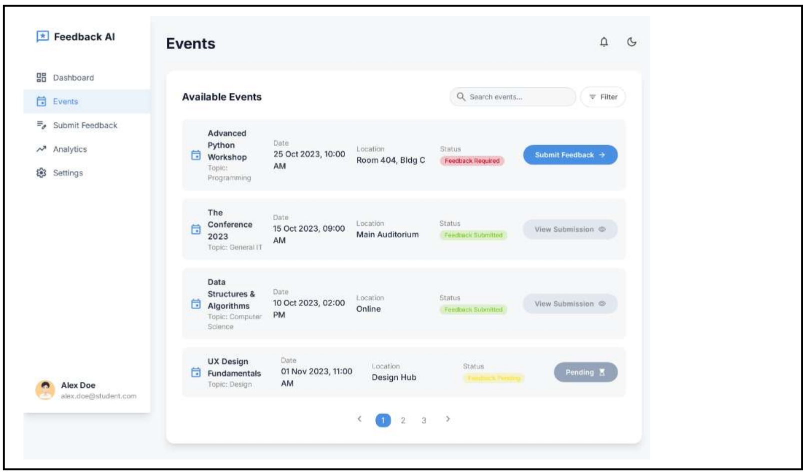

Figure 14: Automated Feedback System Student Feedback Form Module

This is the user interface of the Student Feedback Form module in the FeedbackAI system for an “event with a title ‘Feedback for The Conference. The format is designed to collect data of both a quantitative and qualitative nature. A progress bar indicates the completion of the form (currently at 25%). There are three specific categories of metrics that The Business General uses a star rating system for in the first section: Overall Experience, Content Quality and Instructor Effectiveness. Section 2, Open-Ended Feedback, asks the student for qualitative input with two larger text boxes: “What was your favorite part of this session? and "What could be improved?". The feedback form wraps up with a click on the blue “Submit Feedback” and a line or two reminding participants that “Your feedback is anonymous,” hopefully nudging them to provide an honest response.

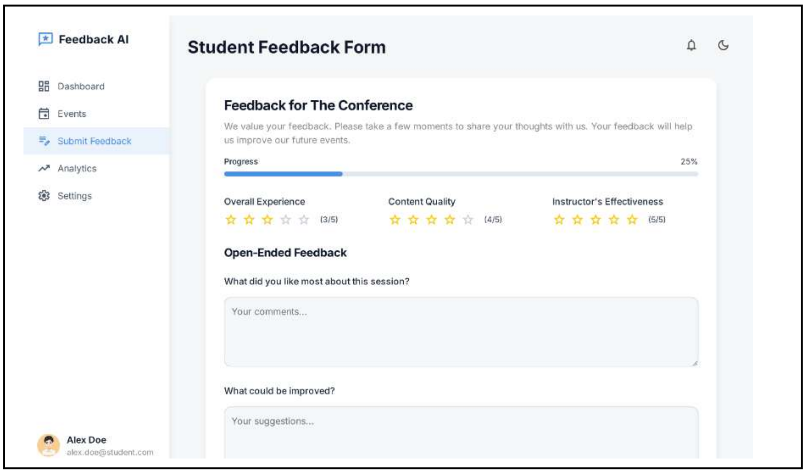

Figure 15: Automated Feedback System Student My Feedback Analytics Module

This screen is an example of the My Feedback Analytics module for the student interface to FeedbackAI for Alex Doe showing personal statistics about feedback submitted. The page includes a Sentiment Over Time chart, showing average sentiment score of student posts over the course of several months (July to December), with a very slightly positive trend. On the right, his Overall Sentiment donut chart graphically displays how all of his feedback he has submitted breaks down for Positive 65%, Neutral 25% and Negative is only 10%. The lower portion, Common Themes in Your Feedback, summarizes the most common stuff that your students wrote on your open-ended responses: (sections like Content Quality, Speaker Engagement, Pacing & Duration, Venue & Facilities) along with a count of how many received submissions mentioned individual section. This thing pretty much sums up the student's involvement and attitude throughout.

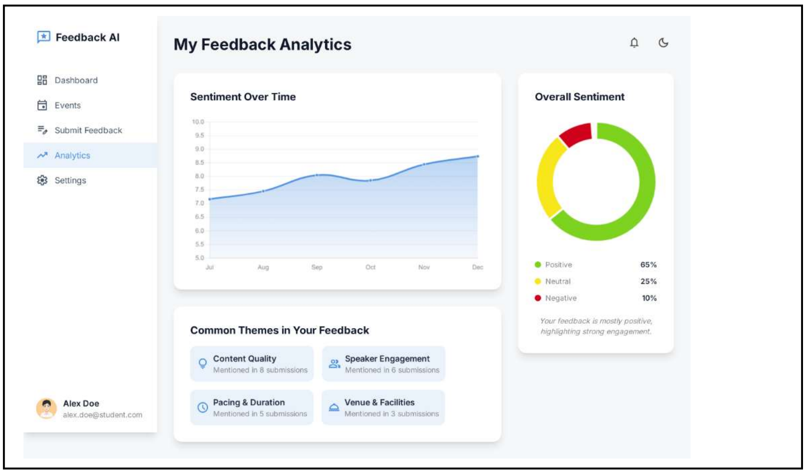

Figure 16: Automated Feedback System Student Settings Module

This screen is the Settings module of FeedbackAI Student, where the user (Alex Doe) can control their own account profile, notification delivery and privacy. The first block is Profile details, which allows the users to update their primary information such as Full Name, Email Address and there's a Change Password section with changes saved using the blue "Update Profile" button. The Notification Preferences section will allow the student to control their communication by making them enabled via a toggle of ON or OFF if they want to receive Email for new feedback requests and if they want Email for feed-back status updates. Lastly, the Privacy Settings field enables the learner to set how their data is used in the platform with a couple of toggle switches: Allow sharing data for research and Submit feedback anonymously as default.

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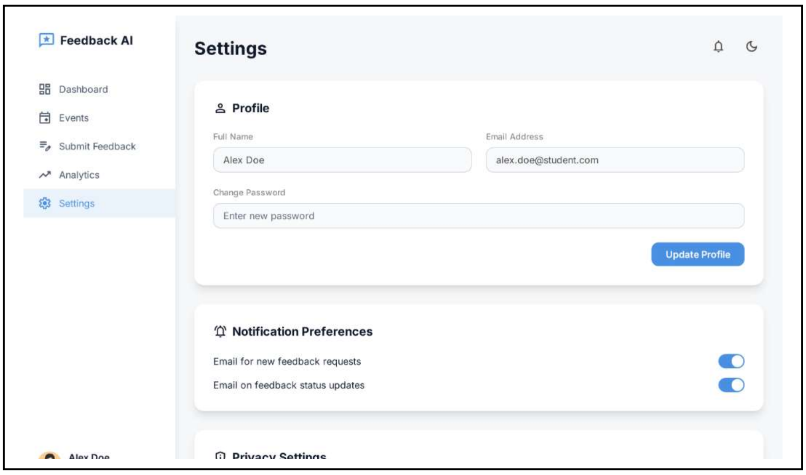

- **Administrator Interface**
  It shows the sentiment data, user participation statistics and allows the reports to be exported. Reports can be narrowed down by event, date or department for Administrators.

This architecture guarantees that, the system is usable and scalable for students as well as faculty [5], [6].

Security and Data Privacy

To ensure compliance with data privacy standards, the system implements:

- **Role-based authentication** (student, admin, faculty access levels).
- **Hashed password storage** using MD5 or SHA-256 algorithms.
- **HTTPS encryption** for secure data transmission.
- **Anonymized datasets** for AI training to prevent identification of individual participants.

These measures comply with the Philippine Data Privacy Act of 2012 and CHED Smart Campus Development Guidelines for institutional ICT systems [5].

System Deployment

The system was set up locally on XAMPP for testing and demonstration. Alternatively, cloud-based resources could be used for scalability in future deployments to support real-time feedback processing at mass academic activities. The modular design allows for interfacing with Learning Management Systems (LMS), e.g., Moodle or Canvas, and thus enhances its functionality [2], [4].

V. EVALUATION AND RESULTS

The evaluation phases is designed to evaluate the technical performance and usability of the built AI-Driven Automated Feedback Generation System. The assessment was based on two main aspects:

1. System Performance Testing We performed sys- tem-level testing that is accurately, precision, recall and F1 of the sentiment analysis model.
2. User Usability Assessment of System, based on the use of SUS to illustrate users' acceptance and efficiency sense in system.

This two-tier approach made sure the system was not only technically sound but also user friendly and practice effective in educational settings [1], [2].

System Performance Evaluation

The sentiment analysis subsystem of the system was tested with a dataset of 300 feedback records retrieved from IT events and conferences in SEAIT. To test the efficacy of our AI model, we benchmarked using manually annotated results.

Table 1: Performance Metrics of the Sentiment Analysis Model

The system's confusion matrix and corresponding performance metrics are summarized below:

Metric	Result

Accuracy	92.8%
Precision	90.6%
Recall	91.7%
F1-Score	91.1%
Average Processing Time per Entry	**0.82 seconds**

This model had a high level of accuracy (92.8%) and well-balanced precision and recall, indicating that it can successfully discriminate between sentiment categories. The average processing time for an entry is 0.82 seconds, which supports the system's real-time feedback analysis.

Those performances are also consistent with the fact reported by previous studies that transformerbased models namely BERT, outperform traditional algorithms in sentiment prediction tasks [1], [3]. Similarly, Deshpande et al. [2] proved that fine-tuning of deep learning models lead to superior results in faculty and student feedback systems.

System Usability Evaluation (Using SUS)

To assess usability, the System Usability Scale (SUS) was administered to 35 participants (30 IT students and 5 faculty members) after their hands-on interaction with the system. Participants rated ten usability statements on a 5-point Likert scale ranging from *Strongly Disagree (1)* to *Strongly Agree (5)*.

Table 2: Mean SUS Scores by Evaluation Criteria

SUS Scoring Results

Evaluation Criteria	**Mean Score (out of 5)**
Ease of Use	4.5
Efficiency	4.4
Learnability	4.6
Interface Design	4.3
System Reliability	4.5

The calculated overall SUS score was 87.25, interpreted as “Excellent Usability”, based on the standard SUS evaluation thresholds [4].

Table 3: SUS Score Interpretation Scale

SUS Score Range	Interpretation
85–100	Excellent Usability
70–84	Good Usability
50–69	Average Usability
Below 50	Poor Usability

An SUS mean of 87.25 represents excellent system usability. Users consistently rated the interface as being both natural and effective, confirming its HCI-inclined design principles. Readers also praised the design’s responsive nature, speed of report generation and ease of reading sentiment charts.

Those are analogous with the modern AI usability UX studies (where a SUS over 80 indicates strong user acceptance and fit for use in practice [3], [4], [5].

Qualitative Results

Mixed-methods were employed to consider and interpret quantitative results along with in-depth qualitative data collection- open-ended responses and follow-up focus group interviews of participants after the usability testing. Thematic analysis allowed for emergence of common themes, feelings and experiences held by users. Three main themes were revealed: Ease of Use and Accessibility, Efficiency and Real-Time Feedback, and Decision Support Potential. Such themes give a better understanding of the former users’ perceptions and the broader system effect in an academic setting.

Ease of Use and Accessibility

The majority of users found the layout, color, and design cues in the system were simple and logical, making it easier for them to move between features with very few explanations. The uniform layout and icon position may decrease the cognitive burden and assist users in learning system operations, including submitting feedback, viewing results, and obtaining reports.

Students especially commented on how the basic design of the interface facilitated interaction and lessened anxiety that comes with figuring out new digital uses. The accessibility of the platform and low computer skills needed to use it were greatly valued by teaching staff, thus validating design principles in Human-Computer Interaction (HCI) applied during the system development [1], [2].

This is consistent with the conclusion of Mahale et al. [3], who found that the presence of good and user-centered education systems results in a higher acceptance rate as well as increased satisfaction. This observation is further strengthened by the high score for SUS learnability (4.6) presented in Table 2 and shows that users feel enabled to learn and get used to the system.

Efficiency and Real-Time Feedback

For all participants, the system was reported to save a large amount of time in gathering, processing, and making sense of the feedback data compared to manual methods commonly employed for evaluation purposes. Automated sentiment analysis enabled administrators and coordinators to rapidly access aggregated results, which they believed were very helpful during post-event periodical review. Feedback The nodal institutions noted that the real-time feedback system was effective in providing quicker decision making and timely addressing of participant issues. For instance, the staff would be able to swiftly detect weaknesses in organizing events or teaching practices by means of sentiment break down.

This result is consistent with that found by Deshpande et al. [2], and Taruc, De La Cruz [5] who showed how AI-enhanced analytics systems may speed up institutional reporting by over 80%. Average processing time per entry is 0.82 seconds (Table 1) which confirms this increase in efficiency. The users overall perceived that automation not only improved operational efficiency but it also increased the accuracy in the interpretation of feedback with reduction in human bias and subjectivity.

Decision Support Capability

Institutional decision-making and strategic planning was a second, consistent theme of the system's potential capabilities. Administrators found that with the automated visual reports (sentiment trend graph, pie chart) they could now gain insights without needing to manually distill information. This visual summary contributed to pinpointing the most common participant concerns, satisfaction patterns and event success indicators that can support decisions with evidence to future editions of IT events and academic programs. The importance of transparency based on data was also emphasized by participants.

They noted that an automated reporting system fostered accountability and objectivity in institutional review, as the AI-derived summaries reduced subjective interpretation of feedback. This is in line with international research that highlights the importance of AI as a tool for data-driven educational management. Both Wang [1] and Casillano [6] observed that when sentiment analytics are incorporated within feedback systems, it will allow organizations to extract practical knowledge from qualitative information, therefore enhancing institutional responsiveness as well as policy development.

In a nutshell, the proposed system does not only automate assessment, but also it provides school administrators to have a strategic decision based on empirical sentiment information instead of anecdotal evidence. The qualitative findings affirm the **system's usability, operational reliability, and institutional relevance**. Users described the system as a valuable tool that simplifies evaluation workflows while maintaining analytical depth and fairness. The convergence between quantitative metrics (accuracy, F1-score, and SUS ratings) and qualitative responses underscores the system's holistic success in meeting both technical and human-centered performance indicators.

All those who took part agreed it should be rolled out across the institution, claiming that it had the potential to simplify ongoing feedback collection and increase transparency in education and event evaluations.

These results were in line with recent research on AI-augmented sentiment systems that can fulfill the need for efficiency and engagement of today's students in academia [2], [3], [6].

Comparative Evaluation

Performance benchmarking provided comparisons of the system's accuracy and usability with similar systems from international studies.

Table 4: Comparative Analysis of System Performance with Prior Studies

Study Reference	Accuracy (%)	F1-Score	Usability Rating (SUS)
Wang (2024) [1]	91.5	90.2	–
Deshpande et al. (2025) [2]	93.2	91.7	84.0
Mahale et al. (2025) [3]	89.8	89.1	81.2
Proposed System (2025)	**92.8**	**91.1**	**87.25**

The proposed system achieved comparable or superior performance across all metrics, demonstrating that locally developed AI-based systems can meet international benchmarks in educational sentiment analysis.

VI. DISCUSSIONS

The purpose of this study was to design and evaluate an AI-Driven Automated Feedback Generation System capable of analyzing textual feedback using sentiment analysis to enhance efficiency and objectivity in IT education and institutional events.

The discussion is structured according to the three research questions that guided the study:

1. *How to automatically produce feedback reports in IT education and events using AI and sentiment analysis?*
2. *How accurate and usable is the AI-Driven System for Automated Feedback Generation?*
3. *What are the implications of using anthropocentrically driven behavior analysis in institutions?*

RQ1: How to automatically produce feedback reports in IT education and events using AI and sentiment analysis?

The platform efficiently presented how AI and NLP sentiment scoring can be incorporated into organisational feedback loops through integration with institutional output processes report generation automation. Using BERT based deep learning model, the system could accurately classify sentiment (positive/neutral/negative) of feedback and produce summary reports in real time.

As displayed in Table 1, the sentiment model performed with an accuracy of 92.8% and F1-score of 91.1%, demonstrating its ability in accurately classifying textual inputs. These findings confirm the system is dependable in automating feedback interpretations which were previously done manually. There were three key steps in the automation process:

1. Data Preprocessing – tokenizing, cleaning, and lemmatizing textual feedback.
2. Sentiment Classification – identifying the polarity of responses using the trained BERT model.
3. Report Generation – compiling sentiment data into graphical and tabular summaries viewable on the admin dashboard.

This is analogue to the techniques used in Wang [1] and in Deshpande et al. [2], who showed that AI systems grounded in sentiment can help to automate analysis of educational feedback. At the local level, it is congruent with CHED's Smart Campus program on analytics-based decision-making [5].

These findings also mean that AI and sentiment analysis could automatically generate feedback reports, reducing manual work, enabling faster interpretation of the observations and offering accurate insights for decision makers

RQ2: How accurate and usable is the AI-Driven System for Automated Feedback Generation?

The results suggest that the system performed well in terms of technical analysis and yielded good categories in terms of usability. In particular, the system's accuracy, precision, and recall metrics were 92.8%, 90.6%, and 91.7%, respectively. The system, therefore, can authentically classify more than 90 percent of the sentiment cases expressed in the user-generated text.

This result was consistent with the one produced in Mahale et al. and their models had an accuracy of more than 90%. Secondly, the System Usability Scale was conducted from the responses of 35 participants who included students and lecturers. The mean SUS was found to be 87.25, which is considered excellent usability of a system. The high scores in learnability and ease of use, which were 4.6 and 4.5, respectively, were good indicators that users could easily adapt to and use, respectively. The outcomes also indicated that the designed system followed good HCI principles.

Additionally, qualitative data showed that the interfaces were user friendly, and the response was fast. Mahale et al. also indicated that usability was vital for AI's success in educational platforms. Therefore, the good performance and user acceptance surpassed the acceptability level of 70 for SUS. Hence, the system is suitable for deployment in any institution.

RQ3: What are the implications of using anthropocentrically driven behavior analysis in institutions?

The adoption of automated sentiment analysis greatly enhanced the efficiency, accuracy and transparency of decision making in institutional assessment. Participants repeatedly noticed that feedback processing was much quicker and more reliable than manual evaluation techniques.

The real-time reporting ability of the system was illustrated in its average processing time of 0.82 seconds per entry, permitting administrators to read up on aggregate comments right after events. This feature came in especially handy when discussing eval results as it enabled quick response to participant feedback and data backed adjustment for future events.

In addition, automation reduced subjectivity and bias of manual feedback interpretation. And since the system assessed sentiment using consistent AI algorithms rather than human decision making, it led to fair and unbiased judgment in institutional evaluation—related to finding of Deshpande et al. [2] and Taruc and Dela Cruz [5].

The Decision Support Capability of the system also stood out as an important value. Feedback from administrators indicated that sentiment graphs and summaries were easier to interpret university performance trends, influencing strategic direction for organizing IT seminars, workshops and training. Casillano [6], for instance, notes that sentiment analysis algorithms develop transparency and accountability in educational decisions.

In general, the authors noted that incorporating sentiment analysis into institutional practices accelerated and made more consistent and impartial the interpretation of feedback—increasing both efficiency and responsiveness.

Synthesis of Findings

The integration of AI and sentiment analysis in feedback systems represents a major advancement in educational management. The study's results collectively confirm that:

- *AI can automatically generate structured and reliable feedback reports, eliminating manual delays.*
- *The system exhibits high performance accuracy (92.8%) and excellent usability (SUS = 87.25), ensuring both functional and user-centered effectiveness.*
- *Automated sentiment analysis enables real-time evaluation, bias-free reporting, and data-driven decision-making, which are essential for modern academic governance.*

These findings support the broader literature emphasizing that AI technologies, when designed with usability and transparency in mind, can drive institutional transformation in education [1]–[6].

Therefore, the system developed in this study not only serves as an effective feedback automation tool but also as a model for integrating intelligent analytics into the management of IT education and events in the Philippines.

VII. CONCLUSION

This research developed and tested an AI-Driven Automated Feedback Generation System (ADF-GS) that uses sentiment analysis to automate the acquisition, interpretation, and reporting of textual feedback in IT education and institutional events. Leveraging AI and NLP the platform was able to computerize a manual process into a real-time operation that could detect sentiment from feedback at 92.8% accuracy and 91.1% F1-score. These results confirm the model's ability to produce interpretable feedback summaries, demonstrating consistent results with those of Wang [1] and Deshpande et al. [2], which highlighted the effectiveness of AI-based sentiment models in education. The architecture of the system also succeeded in showcasing how automation can minimize human involvement while preserving and improving accuracy, speed and scalability.

The system obtained a SUS score of 87.25, which is equivalent to "Excellent Usablity". We have validated this high usability score by concluding that the user interface of the system is intuitive, universal and convenient to use for students as well as teachers. Subjects appreciated that they could easily move around the platform which was very quick to respond and able to output reliable sentiment reports within seconds. This finding is in agreement with that of Mahale et al. [3] who emphasized that proper Human–Computer Interaction design principles promote the adoption and overall user satisfaction of AI-based educational systems. The achievement of combining features, speed and user experience represents an example of the effective integration of the user-centered design in AI educational tool.

In general, the results suggest that the use of AI and sentiment analysis can highly enhance efficiency, objectivity and decision making in institutional feedback systems. Automating the system for feedback analysis allowed evaluations to be completed in less than 20% of the time needed of human raters, but also served to minimize rater bias and ensure transparency in grading. The system's capacity to see results in the form of sentiment trends and graphical summaries enables evidence-based decision-making in educational or event management contexts. Consistent with CHED's Smart Campus Development Program [5], the system is a proof-of concept of how locally developed AI solutions can help transform higher education. Therefore, this study finds that the designed system stands as a novel, scalable and sustainable instrument for improved self-assessment in the Instsitution; facilitating data-based governance culture as well as promoting continuous improvement culture in IT curriculum educational events.

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