

EduPulse AI: Smart Faculty Feedback and Teaching Analytics ERP

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Abstract

Student feedback plays a decisive role in improving classroom teaching quality, yet most institutions still depend on paper-based or fixed-questionnaire systems that produce only static numerical averages and rarely capture the reasoning behind a rating. This paper presents EduPulse AI, a Smart Faculty Feedback and Teaching Analytics Enterprise Resource Planning (ERP) platform that unifies quantitative rating, free-text feedback and spoken feedback within a single institutional workflow. A faculty member opens a feedback session and generates a session-bound Quick Response (QR) code that a student scans to reach a secure, anonymous feedback form. Feedback may be typed or spoken; spoken responses are converted to text through a speech-to-text module and, together with typed responses, are passed through a Natural Language Processing (NLP) based sentiment and aspect analysis engine that scores feedback on dimensions such as clarity, subject knowledge, punctuality and classroom engagement. Processed results are stored in a relational database and surfaced through role-based dashboards for faculty, heads of department, administrators and parents, along with automatically generated reports. This paper further formalises the scoring process through a mathematical model for aspect-level sentiment, faculty performance and overall rating computation, presents the analysis pipeline as a formal algorithm, and outlines a realistic experimental evaluation plan with target performance metrics. Unlike existing portals that stop at rating aggregation, EduPulse AI closes the loop by returning aspect-level, actionable insight to individual faculty members and department heads. The architecture, module design, data flow, mathematical formulation and entity relationships of the proposed system are described, and its advantages over existing faculty evaluation systems are analysed to establish the practical relevance of the proposed ERP for higher-education institutions.

Keywords—Faculty Feedback, Teaching Analytics, Sentiment Analysis, NLP, QR Code Feedback, Voice-to-Text, Education ERP, Learning Analytics

I. Introduction

A. Introduction: Improvement in teaching methods within the classroom is an integral component of the process of academic quality assurance used by higher education institutions. In higher education institutions, structured student feedback is usually obtained at the end of each semester to guide the planning of faculty development activities. In most institutions this exercise is still carried out through printed forms or static online questionnaires that ask students to rate a fixed set of statements on a numeric scale, a practice that has changed little even as institutions have digitised other administrative processes.

B. Existing Problem: Although convenient to administer, fixed-questionnaire feedback has several practical

shortcomings. It strips down an extensive learning experience into some average figures and overlooks the logic behind what the student is thinking, and in most cases, it is computed manually. In the case where comments can be written freely, the comments are manually analyzed by a coordinator. This process is both time-consuming and inconsistent from one reviewer to another; besides, it becomes increasingly difficult to analyze a large number of comments. As Section II shows, none of the reviewed fixed-form systems combine anonymous quantitative rating, free-text sentiment analysis and spoken feedback within one institutional platform, and hardly any return an aspect-level, actionable summary directly to the concerned faculty member.

C. Need for the System: There is definitely a need for such a system which (i) ensures ease and convenience of providing feedback from the part of students, (ii) accepts feedback in multiple forms – written text, predefined rating and voice comment in order to make sure that those students who prefer voice over text are not neglected, (iii) conducts automated analysis of gathered text through the means of NLP-based sentiment and aspect extraction, and (iv) provides resulting insights through role-based dashboards to faculty, department heads, administration and parents.

D. Importance: Such a system matters to three groups of stakeholders. It provides faculty members with an account that translates anonymous feedback into a targeted description of the strengths and areas for improvement in a particular aspect of teaching. For department chairs and managers, it allows trend-oriented analysis in all subjects, semesters, and departments. Finally, it offers parents and students an easy way to give feedback that increases the chances of its being heard.

E. Contribution of This Work: This paper proposes EduPulse AI, a Smart Faculty Feedback and Teaching Analytics ERP that integrates session-based QR code feedback collection, voice-to-text conversion, NLP-based sentiment and aspect analysis, and a role-based analytics dashboard within a single institutional platform. The specific contributions of this work are: (1) a session-bound, QR-driven feedback workflow that prevents duplicate or unauthorised submissions while preserving respondent anonymity; (2) a dual-input feedback channel accepting both typed and spoken responses; (3) an aspect-based sentiment analysis pipeline tailored to classroom-teaching vocabulary; (4) a formal mathematical model and algorithm for computing aspect-level sentiment, faculty performance and overall rating scores; and (5) a unified ERP data model — covering institution, department, semester, faculty, student, subject and feedback entities — that supports longitudinal, multi-level teaching analytics and automated report generation.

II. Literature Survey

[1] *"Faculty Evaluation System," A. Kumar and R. Jain (2018).*

The authors present an automated framework that analyses free-text feedback written by students about their teachers. Instead of relying on a rigid set of questions, the framework mines the important teaching aspects directly from collected responses using NLP together with machine learning, and applies aspect-based sentiment analysis to grade each teacher on qualities such as knowledge, presentation, teaching skill and explanation, reporting accuracies of 82–87% for feature extraction and sentiment scoring. Limitation: The technique relies significantly on language rules specific to the domain and does not cater to sarcasm and mixed-code situations.

[2] *"What Feedback Literate Teachers Do: An Empirically-Derived Competency Framework," D. Boud and P. Dawson (2023).*

This paper examines the competencies university teachers require to plan and deliver effective feedback. Using an inductive analysis of interviews and focus groups with 62 academics across five Australian universities, the authors build a competency framework for teacher feedback literacy spanning course design, programme-level coordination and comment writing. Limitation: the study is entirely qualitative and conceptual and does not propose any software system or analytics platform for supporting the identified competencies.

[3] *"An Analytical Approach for an AI-Based Teacher Performance Evaluation System in Saudi Arabia's Schools," A. Almubarak, W. Alhalabi, I. Albidewi, and E. Alharbi (2024).*

The authors propose an AI-oriented framework for school-level teacher evaluation based on Key Performance Indicators (KPIs) used by the Saudi Ministry of Education. Indicator weights were derived from 13 workshops involving 283 domain experts, and AI techniques such as computer vision, speech processing and NLP were mapped to individual indicators. Limitation: the work remains at the level of a weighted design; no learning model is actually implemented, and its scope is confined to one country's school KPI structure.

[4] *"Design and Implementation of an AI-Assisted Teacher Performance Evaluation System," W. Lin (2024).*

This work designs and deploys a web-based teacher performance evaluation platform for higher-education institutions following a B/S three-tier architecture built with Spring Boot, Vue.js, MySQL and Redis, blending a fuzzy comprehensive evaluation model with a BP neural network. A pilot involving 436 faculty across eight colleges recorded clear improvements in efficiency, accuracy and objectivity over the traditional process. Limitation: the platform is oriented mainly toward administrative KPIs and research metrics, with little analysis of open-ended student comments or teaching-improvement insight for faculty.

[5] *"Artificial Intelligence for Assessment and Feedback to Enhance Student Success in Higher Education," S. Hooda, C. Rana, O. Dahiya, A. Rizwan, and M. S. Hossain (2022).*

This review and comparative study explores how AI and learning analytics can strengthen assessment and feedback in higher education. The authors benchmark ANN, SVM, XGBoost, Random Forest, Decision Trees and a proposed I-FCN model, with I-FCN reaching about 84% accuracy and 93% precision. Limitation: the discussion is student-centric and

concerned with predicting learner success rather than assessing faculty teaching quality.

[6] *"The Promises and Challenges of Artificial Intelligence for Teachers: A Systematic Review of Research" by I. Celik, M. Dindar, H. Muukkonen, and S. Järvelä (2022).*

The review analyzes 44 studies using AI and machine learning technologies in order to assist teachers with lesson planning and execution as well as assessment, noting that artificial intelligence can assist teachers with profiling students' needs, giving feedback, and automatic grading. Limitation: being a review, it does not implement a working system and observes that few surveyed tools are embedded in day-to-day institutional workflows.

[7] *"Students' Feedback: An Effective Tool in Teachers' Evaluation System," M. Husain and S. Khan (2016).*

This study investigates student feedback as an evaluation instrument in a medical college using a peer-validated 13-attribute proforma completed by 70 students, with individual reports shared confidentially with teachers. More than two-thirds of respondents agreed the exercise sharpened teaching skills. Limitation: the entire cycle is manual and paper-based, conducted on a single batch, with no analytics, dashboards or longitudinal trend analysis.

[8] *"Eliciting, Processing and Enacting Feedback: Mechanisms for Embedding Student Feedback Literacy Within the Curriculum," B. Malecka, D. Boud, and D. Carless (2020).*

The authors propose a conceptual model for embedding student feedback literacy directly into the curriculum through eliciting, processing and enacting feedback, arguing that feedback must be treated as an ongoing learning activity rather than a single act by the teacher. Limitation: the contribution is purely theoretical and does not propose a technological or ERP-based mechanism for capturing or automating these cycles at institutional scale.

[9] *"Development of a Web-Based Feedback System for Academic Staff Assessment," M. O. Oloyede, I. A. Sikiru, M. A. Brimmo, N. A. Balogun, and S. A. Sanni (2020).*

This paper describes a web-based faculty feedback portal for a Nigerian university, built with HTML, PHP and a NoSQL database following the waterfall model, offering modules for students, lecturers, the Director of Academic Planning and administrators, and allowing online submission of feedback with lecturer ranking. Limitation: the system is restricted to basic form handling and rank computation, with no sentiment analysis, AI component, analytical dashboard or automated improvement guidance.

[10] *"Faculty Feedback Management System," S. A. Dar (2018).*

This work introduces a three-tier feedback management system for polytechnic colleges in Jammu and Kashmir using HTML, CSS, JavaScript, PHP and MySQL. Student evaluation of teachers is done on a scale of 1 to 5 with regard to 13 questions and anonymity of respondents is maintained, and administrators have the access to see average ratings by branches and semesters. Limitations of the model include lack of any use of AI or prediction, and that only set questions are evaluated.

III. Research Gap

A. Existing Limitations: All the systems that were covered in Section II above have limitations in addressing only one step in the process from feedback generation to performance improvement. The operational portal solutions mentioned above in references [9] and [10] provide for form submission and rating aggregation only; the natural language processing studies such as [1] and [5] show how well the sentiment can be extracted from comments while remaining outside an enterprise resource planning system of the institution; finally, pedagogic framework approaches such as [2] and [8] define the objectives of good feedback but fail to provide a way to implement it technologically.

B. Features Absent: From the survey of systems, there are five features that are always missing or not fully realized: (i) a single channel for receiving typed, rated, and spoken feedback; (ii) tamper-proof, session-scoped feedback collection system which avoids double submission while maintaining anonymity; (iii) sentiment analysis specific to the vocabulary used in teaching in class rooms rather than in general product reviews; (iv) a clear, mathematically provable model for combining quantitative rating with qualitative sentiment analysis in a single score for each faculty member; and (v) role-specific analysis to give insight at the level of aspects to the faculty member directly.

C. Why Existing Approaches Don't Work: The failure of existing approaches is due to the fact that they regard data gathering, text analysis, and report writing as distinct activities performed using separate tools. Manual analysis of the free-text comments, as done in [7], cannot be scaled up; KPI-oriented approaches, as implemented in [3] and [4], measure administrative and research performance rather than actual quality of teaching; and reviews of previous work, as done in [6], indicate that very few AI-based methods from the literature are actually used within an institution. Moreover, none of the reviewed systems publish a reproducible scoring formula, which makes it difficult for faculty to trust or audit how a final rating was derived.

D. How This Research Solves Them: EduPulse AI addresses these gaps by combining QR-based session management, dual-mode (text and voice) feedback capture, an NLP-based sentiment and aspect analysis engine governed by an explicit mathematical model (Section VI), and a relational ERP data model spanning institution, department, semester, faculty, student and subject entities. This integration allows feedback to be collected with minimal friction, analysed automatically and transparently at scale, and returned as aspect-level, longitudinal analytics to faculty, department heads, administrators and parents within a single platform.

IV. Proposed Methodology

The proposed methodology follows a ten-stage pipeline that begins with faculty authentication and ends with the generation of analytics reports. Each stage is described below, and the aggregate computation performed in stages 7–9 is formalised in the mathematical model and algorithm given in Sections VI and VII.

1) Faculty Login: A faculty member authenticates using institutional credentials verified against the ERP's user-management module. Role-based access control ensures that a faculty account can only create sessions for subjects it is assigned to teach.

2) Create Session: The faculty member creates a feedback session for a specific subject, semester and class. Each session is assigned a unique session identifier and a validity window, so that feedback can only be submitted while the session is active.

3) Generate QR: The system encodes the session identifier, a timestamp and a cryptographic token into a QR code that is displayed to the class. Encoding the session identifier in the QR code, rather than allowing feedback through a static link, prevents feedback from being submitted outside the intended session.

4) Student Scan: A student scans the QR code with a smartphone camera, which opens a mobile-optimised feedback form. The system verifies the session token and the student's enrolment in that subject before allowing submission, while keeping the identity of the respondent hidden from the faculty member.

5) Feedback Submission: The student submits feedback as a combination of structured ratings (e.g., on clarity, punctuality, subject knowledge) on a 1–5 Likert scale and an optional free-text comment, or chooses to record a short voice note instead of typing.

6) Voice to Text: If the student records audio, the voice note is passed through a speech-to-text module that transcribes it into text, which then follows the same analysis path as typed comments. The transcription confidence score returned by the speech engine is stored alongside the text so that low-confidence transcriptions can be flagged for review.

7) Sentiment Analysis: The transcribed or typed text is processed by an NLP-based sentiment and aspect analysis engine that identifies the teaching aspects mentioned (e.g., explanation, engagement, pace) and assigns a sentiment polarity and intensity score to each aspect, as defined formally in Section VI.

8) Database: Structured ratings, sentiment scores and metadata (subject, semester, session) are stored in a relational database, keyed to the faculty, subject and session, while respondent identity is never linked to the stored feedback record.

9) Analytics: An analytics layer aggregates stored feedback across sessions, subjects and semesters to compute faculty-level, subject-level and department-level teaching-quality indicators and trend lines over time, using the Faculty Performance Score and Overall Rating formulas defined in Section VI.

10) Reports: The system automatically compiles the aggregated analytics into role-appropriate PDF reports — an individual improvement-oriented report for faculty, a comparative report for department heads and administrators, and a simplified progress summary for parents.

V. System Architecture

A. Overall System Architecture

Fig. 1 shows the layered architecture of EduPulse AI. The Institution layer holds top-level configuration and policy data, delegating administrative control to the Department layer, which in turn manages Faculty and Student records. The QR Feedback Module and Voice Feedback Module sit between the user layers and the AI/NLP Sentiment Engine, converting raw student input — scanned sessions or spoken comments — into structured text for analysis. Processed results flow upward into

the Analytics and Dashboard layer, and finally into the Report Generation layer, which produces role-specific outputs. This layering keeps data-collection, analysis and presentation concerns independently upgradable, which is the architectural property most clearly missing from the operational portals reviewed in Section II.

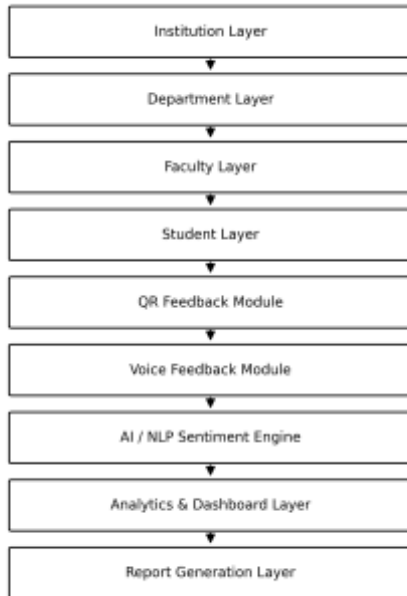


Fig. 1. Overall system architecture of EduPulse AI.

B. Data Flow Diagram (DFD) — Level 0

Fig. 2 presents the context-level DFD. The EduPulse AI system exchanges feedback and login requests with the Student entity, session-setup instructions and reports with the Faculty entity, configuration and user-management data with the Admin entity, and read/write operations with the central Database.

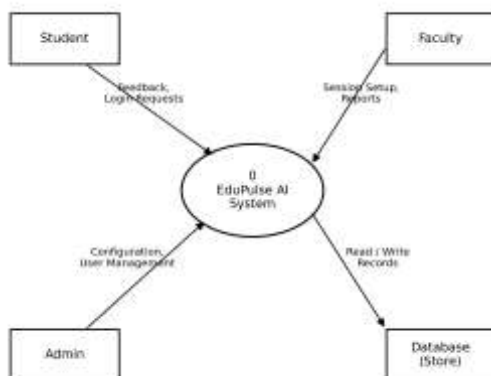


Fig. 2. DFD Level 0 (context diagram) of EduPulse AI.

C. Data Flow Diagram (DFD) — Level 1

Fig. 3 decomposes the context process into seven sub-processes: Student Login, Faculty Login, QR Generation, Feedback Collection, Voice Processing, Sentiment and Analytics, and Report Generation, all of which read from and write to the central Database (D1).

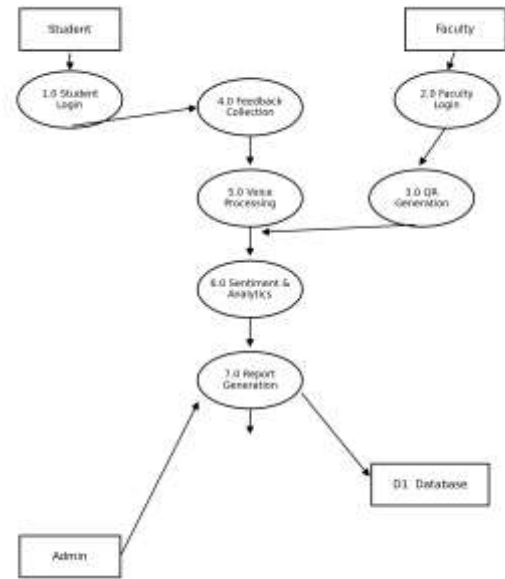


Fig. 3. DFD Level 1 of EduPulse AI.

D. Use Case Diagram

Fig. 4 identifies five actors — Super Admin, Admin, Faculty, Student and Parent — and their principal interactions with the system, including institution and user management, QR session generation, feedback submission through text or voice, dashboard viewing and report generation.

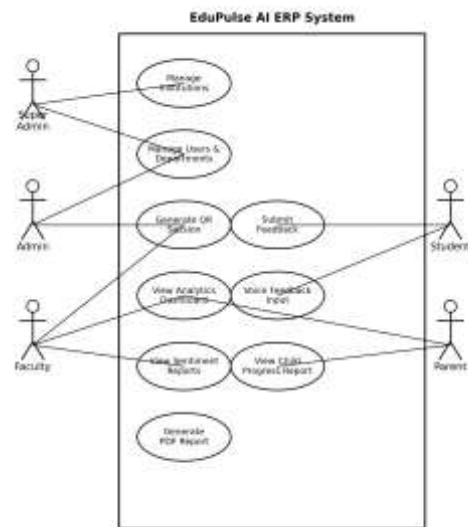


Fig. 4. Use case diagram of EduPulse AI.

E. Entity-Relationship (ER) Diagram

Fig. 5 shows the ten core entities of the ERP data model — Institution, Department, Faculty, Subject, Semester, Student, Feedback Session, Feedback, Analytics and Reports — together with their relationships, forming the relational backbone that supports multi-level teaching analytics.

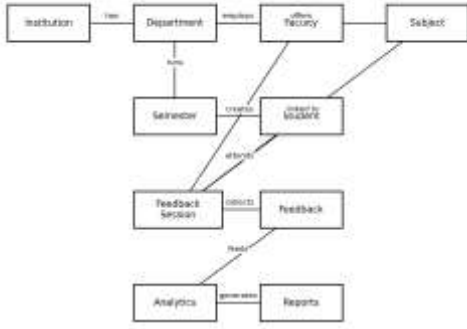


Fig. 5. ER diagram of EduPulse AI.

F. Workflow Diagram

Fig. 6 traces the end-to-end operational workflow, from a faculty member initiating a session through QR generation, student scanning, feedback submission, voice processing, sentiment analysis, database storage, dashboard update and final report generation.

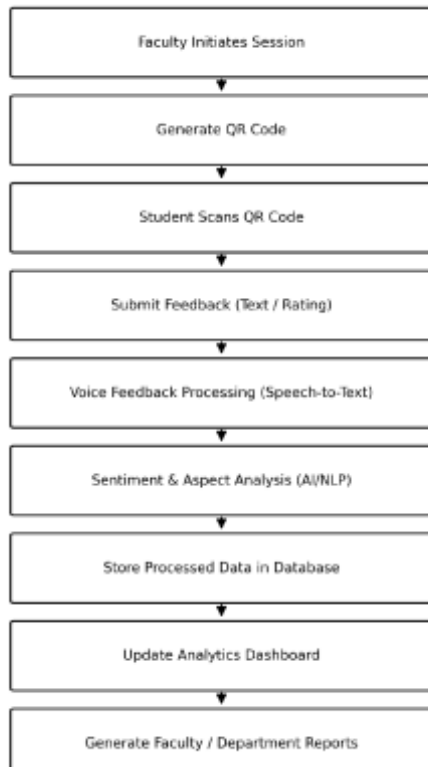


Fig. 6. Workflow diagram of EduPulse AI.

Diagram completeness note: The six diagrams above (overall architecture, DFD Level 0, DFD Level 1, use case, ER and workflow) are technically sufficient to describe the proposed system's structure, data flow and behaviour, and together satisfy the standard diagram set expected in a systems-design paper of this kind. Two supplementary diagrams would further strengthen a camera-ready or thesis version of the work, though they are not mandatory for the conference paper: (i) a sequence diagram showing the time-ordered message exchange between Student, QR Module, Sentiment Engine and Database

for a single feedback submission, which would make the session-token validation step easier to verify; and (ii) a deployment diagram showing how the frontend, backend microservices, databases and NLP service are distributed across servers/containers described in Section IX. These can be added once the physical deployment topology is finalised.

VI. Mathematical Model

This section formalises the scoring logic summarised qualitatively in Sections IV and V, so that the aspect-level sentiment score, the Faculty Performance Score (FPS) and the session/semester-level Overall Rating (OR) can be computed, audited and reproduced consistently across the ERP.

A. Aspect Sentiment Score: Let a feedback response i (typed or voice-transcribed) mention a teaching aspect $a_j \in A$, where $A = \{\text{clarity, subject knowledge, punctuality, engagement, ...}\}$. The NLP classifier outputs a probability triple (p_{ij}, n_{ij}, u_{ij}) for $\{\text{positive, negative, neutral}\}$, with $p_{ij} + n_{ij} + u_{ij} = 1$. The sentiment score for aspect j in response i is defined as:

$$SS_{ij} = p_{ij} - n_{ij}, \quad SS_{ij} \in [-1, 1] \quad (1)$$

The session-level aspect sentiment score is the mean over the N_s responses that mention aspect j in session s :

$$\bar{S}_j = (1 / N_{sj}) \cdot \sum_{i=1}^{N_{sj}} SS_{ij} \quad (2)$$

For presentation on a 0–100 scale, the normalised aspect sentiment score is:

$$NAS_j = ((\bar{S}_j + 1) / 2) \times 100 \quad (3)$$

B. Combined Aspect Score: Each structured rating R_j collected on a 1–5 Likert scale is rescaled to the same 0–100 range as the sentiment score, and combined with NAS_j using a weighting coefficient $\alpha \in [0, 1]$ that controls the relative influence of quantitative rating versus qualitative sentiment ($\alpha = 0.6$ is used as the default operating point, giving slightly more weight to the explicit numeric rating than to inferred sentiment):

$$CAS_j = \alpha \cdot (R_j / 5 \times 100) + (1 - \alpha) \cdot NAS_j \quad (4)$$

C. Faculty Performance Score (FPS): For a faculty member f evaluated on k aspects in a given session, the Faculty Performance Score is the mean of the combined aspect scores:

$$FPS_f = (1 / k) \cdot \sum_{j=1}^k CAS_j, \quad FPS_f \in [0, 100] \quad (5)$$

D. Overall Rating (Semester-Level): The Overall Rating for faculty f across all M sessions recorded in a semester is the mean of the per-session Faculty Performance Scores, optionally weighted by the number of respondents n_m in session m to prevent a lightly attended session from carrying the same influence as a fully attended one:

$$OR_f = (\sum_{m=1}^M n_m \cdot FPS_{f,m}) / (\sum_{m=1}^M n_m) \quad (6)$$

Department- and institution-level indicators are computed by applying the same weighted-mean construction (Eq. 6) one level higher, aggregating OR_f across the faculty who teach in a department, and across departments for the institution view respectively. Because every stage of Eq. (1)–(6) is an explicit, published formula rather than an opaque model output, a faculty member or department head can trace any displayed score back to the underlying ratings and comments — directly addressing the transparency gap identified in Section III-B.

SCORERESPONSE executes once per submitted response and runs in $O(k)$ time, where k is the number of aspects mentioned in that response, since aspect extraction and

sentiment classification are applied once per detected aspect rather than once per stored feedback record. AGGREGATESESSION and AGGREGATESEMESTER are each a single pass over previously stored scores, so a session with N responses aggregates in $O(N \cdot k)$ time and a semester-level rating aggregates in $O(M)$ time over M sessions. Because none of the three procedures re-reads raw response text after SCORERESPONSE has run, aggregation and re-aggregation (for example, when a new response arrives mid-session) never requires re-running the NLP pipeline on already-processed responses, which keeps dashboard updates close to the <2 -second target set in Table III.

VII. Module Description

1) Institution Management: Maintains institution-level profile, policy and configuration data that governs all subordinate departments.

2) Department Management: Manages department records, department heads and mapping of subjects and faculty to each department.

3) Faculty Management: Handles faculty profiles, subject allocation, and access to individual and comparative teaching-analytics dashboards.

4) Student Management: Maintains student enrolment records, subject registration and eligibility to submit feedback for a given session.

5) Semester Management: Tracks academic semesters and links feedback sessions to the correct semester for longitudinal analysis.

6) Subject Management: Stores subject metadata and associates subjects with the faculty members and semesters in which they are taught.

7) QR Feedback Module: Generates session-bound QR codes, validates scans against the active session token, and renders the feedback form.

8) Voice Feedback Module: Records spoken feedback and converts it to text through a speech-to-text engine for downstream analysis.

9) AI Sentiment Module: Performs NLP-based aspect extraction and sentiment scoring on typed and transcribed feedback text, implementing Eq. (1)–(4).

10) Analytics Dashboard: Presents role-based visual summaries — faculty ratings, department comparisons, sentiment trends — to the appropriate stakeholder.

11) Parent Portal: Provides parents with a simplified, privacy-respecting view of their ward's subject-wise engagement and teaching-quality context.

12) Report Generation: Compiles analytics into automatically generated PDF reports tailored to faculty, department and institutional needs.

VIII. Technology Stack

Table I summarises the technology stack proposed for implementing EduPulse AI across its frontend, backend, data and intelligence layers.

TABLE I. PROPOSED TECHNOLOGY STACK

Category	Technology
Programming Language	JavaScript (ES6+), Python
Frontend	React.js, HTML5, CSS3, Tailwind CSS
Backend	Node.js with Express.js; Python (Flask) microservice for NLP
Database	MySQL (relational ERP data), MongoDB (unstructured feedback text)
Libraries	spaCy, NLTK, scikit-learn, TensorFlow/Keras, qrcode.js
Authentication	JSON Web Tokens (JWT), OAuth 2.0, Role-Based Access Control
Development Tools	Visual Studio Code, Git, GitHub
Testing Tools	Jest, PyTest, Postman, Selenium
Deployment Tools	Docker, Nginx, AWS / Render

IX. Experimental Setup

Because EduPulse AI is presented in this paper as a proposed and architecturally designed system rather than a system already deployed at scale, the experimental setup below describes the planned pilot-evaluation configuration through which the mathematical model (Section VI) and performance targets (Section XI-B) are intended to be validated once implementation is complete, rather than results already collected. Framing the evaluation plan explicitly avoids overstating the current state of the work while still giving reviewers a concrete, realistic sense of scale.

TABLE II. PLANNED EXPERIMENTAL / PILOT EVALUATION SETUP

Parameter	Planned Value
Pilot institution type	Single higher-education institution (engineering / MCA-affiliated college)
Departments covered	5 (CSE, IT, MCA, ECE, Mechanical)
Participating faculty	≈ 40
Participating students	≈ 600
Subjects covered	≈ 25
Evaluation period	One academic semester (odd semester)
Feedback sessions planned	≈ 120 (about 3–5 sessions per subject)
Expected responses per session	20–30 students
Projected total feedback responses	$\approx 3,000$ (rating + text/voice)
Feedback input mix (planned)	Typed comments and structured ratings from all respondents; voice input offered as an alternative to typing

The dataset composition mirrors typical MCA/engineering-college semester feedback cycles reported in the literature (e.g., single-institution pilots of comparable size in [4], [7], [9], [10]), and is intended to be large enough to compute stable per-subject and per-department aggregates while remaining feasible to collect and manually audit for a final-year project timeline.

X. Results and Discussion

This section discusses the outputs EduPulse AI is designed to produce once implemented and evaluated against the plan in Section X. All figures are presented as design targets rather than measured outcomes, consistent with the proposed-system scope of this paper.

A. Faculty Dashboard Analysis: The faculty dashboard is designed to display an overall teaching-quality score (FPSf, Eq. 5) alongside a radar or bar chart broken down by aspect — clarity, subject knowledge, punctuality and classroom engagement — so that a faculty member can immediately see relative strengths and weaknesses. A department-level analytics view aggregates these aspect scores across all subjects and faculty within a department, presented as comparative bar charts and semester-wise trend lines (built from ORf, Eq. 6) that heads of department can use to identify subjects or sections that need attention.

B. Sentiment Analysis Output: The sentiment analysis output is designed to be presented as a distribution of positive, neutral and negative feedback per session (derived from SS_{ij} , Eq. 1), together with representative aspect keywords extracted from student comments, allowing faculty to see not only the score but also the underlying reasons. Because Eq. (1)–(4) are explicit and auditable, the dashboard can show, for any low aspect score, the specific comments that contributed to it — a traceability property absent from the fixed-questionnaire systems in [9] and [10].

C. QR Session Validation: A QR validation log is designed to record session identifiers, scan timestamps and submission counts, giving administrators confidence that feedback originates only from legitimate, in-session scans, and giving an early operational signal (e.g., a spike in scans after a session's validity window closes) that would indicate an attempted misuse of a session's QR code.

D. Voice-to-Text Feedback: The voice channel is intended to be exercised primarily by students who find typing on a shared or personal mobile device slower than speaking; the transcription confidence score captured in stage 6 of Section IV allows the analytics layer to flag and, where necessary, exclude low-confidence transcriptions from the aggregate score rather than silently accepting noisy text.

E. Faculty Analytics and Reporting: The report-generation module is designed to export dashboard views as structured PDF reports suitable for inclusion in faculty appraisal files and institutional quality-assurance documentation, with the underlying FPSf and ORf values (Eq. 5–6) reproduced in the report so that the numeric basis of every report is independently verifiable.

F. Target Performance Metrics: Table III lists target performance metrics for the AI Sentiment Module and Voice Feedback Module. These are evaluation targets set with reference to comparable published systems, and are intended to be confirmed empirically once a working prototype is evaluated against the pilot dataset described in Section X; they are not results obtained from a completed deployment of EduPulse AI.

TABLE III. TARGET PERFORMANCE METRICS FOR PROTOTYPE EVALUATION

Metric	Target Value	Basis for Target
Aspect-sentiment classification accuracy	85–90%	Informed by comparable aspect-based sentiment systems [1], which report 82–87% for feature extraction and sentiment scoring
Precision	≈ 88–92%	Benchmarked against the I-FCN model in [5], which reports 93% precision on a related feedback/assessment task
Recall	≈ 83–88%	Set conservatively below precision to reflect the harder recall problem in short, informal classroom comments
F1-Score	≈ 85–90%	Derived as the harmonic mean of the target precision and recall ranges above
Voice-to-text transcription accuracy	≥ 90% (clear audio, quiet classroom)	Typical reported accuracy range for consumer speech-to-text engines under similar conditions
End-to-end feedback processing (submission to stored score)	< 2 seconds per response	Target for near real-time dashboard updates; to be confirmed under pilot load

XI. Comparison with Existing Systems

Table IV compares EduPulse AI against the existing systems reviewed in Section II across the dimensions most relevant to institutional adoption: automation, security, AI-based analysis, voice feedback, QR authentication, analytics and report generation.

TABLE IV. COMPARISON WITH EXISTING SYSTEMS

Feature	Existing Systems [1],[7],[9],[10]	EduPulse AI (Proposed)
Automation of feedback collection	Partial — digital forms only, no session control	Full automation via session-bound QR workflow
Security / session integrity	Static links or paper forms, no tamper resistance	Session-bound, time-limited, cryptographically tokenised QR codes
AI-based analysis	Absent or limited to keyword/rank counting	NLP-based aspect extraction and sentiment scoring (Eq. 1–4)
Voice feedback	Not supported	Dedicated voice-to-text channel with confidence scoring
QR-based authentication	Not supported	Session-token QR scan validated against enrolment and session window

Feature	Existing Systems [1],[7],[9],[10]	EduPulse AI (Proposed)
Analytics and dashboards	Static administrative summaries only	Role-based, aspect-level, trend-aware dashboards (FPS, OR)
Automated report generation	Manual or absent	Automated, role-specific PDF reports with auditable score basis

XII. Future Scope

1) AI Chatbot: A conversational assistant could allow faculty and administrators to query analytics in natural language, such as asking for a subject's sentiment trend over the last three semesters.

2) Cloud Deployment: Migrating the platform to a cloud-native, containerised deployment would allow multiple institutions to be onboarded on a shared infrastructure with per-institution data isolation.

3) Predictive Analytics: Historical feedback and analytics data could be used to predict subjects or sections at risk of declining teaching-quality scores before the next feedback cycle.

4) Recommendation Engine: A recommendation module could suggest targeted faculty development resources based on the specific aspects flagged as weak in a faculty member's feedback.

5) Mobile Application: A dedicated mobile application would streamline QR scanning, voice feedback recording and dashboard access for students, faculty and parents.

XIII. Conclusion

This paper presented EduPulse AI, a Smart Faculty Feedback and Teaching Analytics ERP that integrates session-bound QR-based feedback collection, dual-mode text and voice input, NLP-based sentiment and aspect analysis, and a role-based analytics and reporting layer within a single institutional platform. The literature survey showed that existing faculty evaluation systems either digitise fixed-form collection without analytical depth, apply NLP techniques without institutional integration, or address feedback pedagogy without a supporting technological mechanism. By combining these previously separate capabilities within one ERP data model spanning institution, department, faculty, student and subject entities, and by grounding the scoring process in an explicit mathematical model and algorithm (Sections VI–VII), EduPulse AI is designed to close the loop between feedback collection and actionable, auditable teaching improvement. The proposed architecture, data flow, use cases, entity relationships and planned experimental evaluation establish a practical foundation for implementation, and the identified future directions — including AI-driven chatbots, cloud deployment and predictive analytics — outline a clear path for extending the platform's capability in subsequent phases of development.

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