Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-4 | Issue-5 | May-2026 | Page 729-738

EduTrack: An NLP and Data Science-Based Student Performance Tracking and Enhancement System

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Abstract

The use of Artificial Intelligence (AI) and Natural Language Processing (NLP) in education technology has greatly changed how we keep track of students' academic progress. This paper introduces EduTrack, a browser-based Student Performance Tracking and Enhancement System that evaluates eight essential academic dimensions—namely examination scores, attendance, assignment completion, class participation, study hours, extracurricular involvement, teacher feedback, and self-reported stress levels—to generate a comprehensive performance profile for each student. The system uses a weighted scoring algorithm to figure out an overall academic score. It shows performance data in four interactive Chart.js visualisations and uses the Anthropic Claude API (claude-sonnet-4-20250514) to make personalised NLP-driven assessments and plans for improvement. EduTrack is a lightweight, static web app that shows how AI can be used to help students with their studies. It was made with HTML5, CSS3, and plain JavaScript, and it doesn't need a backend. Experimental observations demonstrate that students receiving multi-dimensional feedback alongside AI-generated personalised recommendations exhibit enhanced clarity regarding their academic status and pathways for improvement, in contrast to those receiving solely traditional grade-based reports.

Keywords: Artificial Intelligence (AI), Natural Language Processing (NLP), Student Performance Tracking, Educational Technology, Personalized Learning Analytics

1. Introduction

Data-driven insights and smart technologies are having a bigger and bigger impact on education in the twenty-first century. Traditional academic evaluation systems, which primarily depend on examination scores as the exclusive indicator of student performance, have faced significant criticism for their failure to reflect the complex nature of learning [1][2]. Factors such as student attendance, participation in classroom discussions, consistency in assignment completion, study discipline, and psychological well-being are recognised contributors to academic success, yet they are predominantly excluded from traditional reporting systems [4].

The fast growth of Artificial Intelligence, especially Natural Language Processing, has made personalised education possible in new ways. AI-powered systems can now look at complicated datasets with many variables and give feedback that is easy for humans to

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understand and takes into account the context. This was only possible before through direct teacher-student interaction [5]. This making personalised guidance available to everyone is especially important in schools where there are a lot of students and not enough teachers to give each one their full attention.

EduTrack was made to fill this important gap. The system collects data from eight academically validated performance dimensions and uses the Anthropic Claude large language model to create a personalised written assessment for each student, along with a six-step plan for improvement. The goal is not to take the place of teachers, but to add to their role by giving students quick, smart feedback that helps them figure out what they're good at, what they need to work on, and how to improve [6].

2. Literature Review

Research in the domain of AI-assisted education has grown substantially over the past decade. Romero and Ventura (2010) provided a comprehensive survey of educational data mining techniques, highlighting the potential of machine learning to predict student performance and enable early intervention [7]. Their work established foundational frameworks for using historical academic data to identify at-risk students, which remains a cornerstone of intelligent tutoring research.

Baker and Siemens (2014) distinguished between educational data mining and learning analytics, noting that while both fields share data-driven approaches, learning analytics places greater emphasis on making insights directly actionable for instructors and learners [8]. This distinction is central to EduTrack's design philosophy, which prioritises the delivery of interpretable, student-facing recommendations over purely predictive modelling.

The application of NLP to education was explored extensively by Litman (2016), who demonstrated that automated natural language feedback could rival human-generated commentary in terms of perceived helpfulness when evaluated by students [9]. More recently, the emergence of large language models (LLMs) such as GPT-4 and Claude has dramatically expanded the quality and contextual relevance of AI-generated educational feedback [10].

Regarding multi-dimensional performance tracking, Fredricks, Blumenfeld, and Paris (2004) established that student engagement — encompassing behavioural, emotional, and cognitive dimensions — is a robust predictor of academic outcomes [11]. This theoretical grounding informed the selection of EduTrack's eight performance dimensions, which span behavioural indicators (attendance, assignments), cognitive indicators (exam scores, study hours), and psychological indicators (stress levels, participation).

Despite these advances, existing commercial student information systems such as Blackboard and Canvas remain predominantly grade-centric and do not integrate AI narrative feedback at the individual student level [12]. EduTrack addresses this gap by combining multi-dimensional data collection, quantitative visualisation, and LLM-powered qualitative assessment in a single, accessible interface.

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3. Problem Statement

Despite decades of research demonstrating the multi-causal nature of academic performance, the majority of educational institutions continue to evaluate students through a narrow, examination-centric lens [2]. This approach creates several well-documented problems:

- Students who perform poorly on examinations due to high stress or low attendance receive no targeted, personalised guidance.
- Teachers lack the time and tools to deliver individualised feedback to every student across all performance dimensions.
- Existing digital platforms aggregate grades but do not synthesise them into human-readable, actionable narratives.
- The correlation between non-academic factors (stress, extracurricular load) and academic outcomes is not visible to students or parents.

The core problem EduTrack addresses is therefore: How can a lightweight, accessible web application collect multi-dimensional student data, visualise it meaningfully, and leverage AI to generate personalised academic guidance without requiring institutional infrastructure or backend servers

4. Proposed System / System Overview

EduTrack is proposed as a client-side web application that operates entirely within the browser, eliminating the need for server infrastructure, database management, or user authentication systems. The system collects student data through an interactive form with eight slider-based input controls representing the identified performance dimensions, and an additional three text fields capturing the student's strongest subject, weakest subject, and personal learning goal.

Upon submission, the system executes a weighted scoring algorithm to compute a single overall academic score on a 0–100 scale, calculates a corresponding letter grade (A+ through F), and dynamically renders a multi-panel results dashboard. This dashboard includes a score banner, four data visualisations, a strengths-and-weaknesses panel, and an AI-generated personalised assessment retrieved from the Anthropic Claude API [13].

4.1 Key Differentiators

- No backend dependency — runs entirely in the browser as a static HTML/CSS/JS application.
- AI narrative generation via LLM API, not rule-based templating.
- Eight-dimensional analysis versus the single-dimension (grade) approach of most tools.
- Personalised action plan generated dynamically from the student's specific metric values.
- Four complementary chart types providing different analytical perspectives on the same data.

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5. System Architecture & Design

The EduTrack application follows a clean separation-of-concerns architecture, organised across three files: *index.html* (structural markup), *style.css* (visual presentation), and *script.js* (application logic). This modular structure is consistent with best practices in frontend software engineering and facilitates independent maintenance of each layer [14].

5.1 Data Flow

The data flow within EduTrack follows a linear pipeline:

- User input is captured from HTML form controls (sliders and text fields).
- JavaScript reads and validates all input values on button click.
- A weighted scoring algorithm computes the overall score and grade.
- Static result components (metric cards, progress bars, strengths/weaknesses) are rendered via DOM manipulation.
- An asynchronous fetch() call is made to the Anthropic Claude API with a structured prompt containing all student data.
- The API response is parsed and rendered as the AI assessment narrative.
- Chart.js renders all four visualisations on HTML5 canvas elements.

5.2 Design Principles

The UI follows a formal academic aesthetic using a navy (#1A2744) and gold (#C8A84B) colour scheme. CSS custom properties (design tokens) ensure visual consistency throughout the interface. The layout is fully responsive, adapting from four-column desktop grids to single-column mobile stacks via CSS media queries [14].

6. Technology Stack

The following table summarises all technologies employed in EduTrack and the justification for each selection:

Technology	Version / Source	Role & Justification
HTML5	W3C Standard	Semantic document structure; native form controls; canvas element for charts
CSS3	W3C Standard	Custom properties (tokens), grid/flexbox layout, animations, responsive design
JavaScript	ES6+ (Vanilla)	DOM manipulation, weighted algorithm, async API calls; no framework overhead

Innovation and Integrative Research Center Journal
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Chart.js	v4.4.1 (CDN)	Canvas-based interactive charts; radar, bar, doughnut types; lightweight
Anthropic Claude API	claude-sonnet-4-20250514	LLM-powered NLP narrative generation and personalised feedback
Google Fonts	CDN	Playfair Display (headings) and Source Sans 3 (body) for academic typography

Vanilla JavaScript was chosen over frameworks such as React or Vue to minimise dependency overhead and ensure the application functions as a true static webpage with zero build tooling. Chart.js was selected over D3.js for its simpler API and built-in responsive behaviour [15]. The Anthropic Claude API was chosen for its superior instruction-following capability and contextually sensitive natural language generation compared to alternatives evaluated during development [13].

7. Methodology

7.1 Selection of Performance Dimensions

The eight performance dimensions were selected through a review of educational psychology literature identifying the strongest predictors of academic achievement [11] [4]. Each dimension was chosen to represent a distinct facet of the student experience: cognitive (exam score, study hours), behavioural (attendance, assignment completion, participation), social (extracurricular activities), evaluative (teacher feedback), and psychological (stress level).

7.2 Weighted Scoring Algorithm

The overall performance score is computed using the following weighted formula:

Overall Score = (Exam × 0.30) + (Attendance × 0.15) + (Assignments × 0.15) + (Participation × 0.10) + (Study Hours × 0.10) + (Teacher Feedback × 0.10) + (Stress Management × 0.10)

Exam score carries the highest weight (30%), reflecting its direct correlation with academic outcomes [7]. Study hours and extracurricular data are normalised to a 0–100 scale before weighting. Stress management is inverted (higher stress yields lower score) to reflect its negative impact on performance [4].

7.3 NLP Prompt Engineering

The AI assessment is generated through a carefully structured prompt submitted to the Claude API. The prompt encodes the student's full metric profile, computed overall score, strongest and weakest subjects, and stated learning goal. The model is instructed to produce three sections: a personalised 3–4 paragraph assessment referencing actual scores, a list of three

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priority improvements, and a motivational closing paragraph. This structured prompt design follows the principle of constraint-based generation, which has been shown to improve the relevance and specificity of LLM outputs in educational contexts [10].

7.4 Visualisation Strategy

Four complementary chart types are used to present the data from different analytical angles: the Radar chart provides a holistic 8-dimensional profile at a glance; the Bar chart enables direct comparison across dimensions with colour-coded performance tiers; the Doughnut chart summarises the proportion of strong, average, and weak dimensions; and the Progress bars offer a linear, scannable view of five key metrics. This multi-chart approach is grounded in information visualisation research that recommends providing multiple coordinated views of complex datasets [15].

8. Implementation

8.1 File Structure

The project is organised into three files:

- index.html — All HTML markup, semantic sectioning, and form controls.
- style.css — Complete design system including CSS custom properties, grid layouts, animations, and responsive breakpoints.
- script.js — All JavaScript logic including slider synchronisation, weighted scoring, DOM rendering functions, Chart.js instantiation, and the Anthropic API fetch call.

8.2 Key Implementation Modules

The JavaScript codebase is organised into ten modular functions:

- syncSlider() — Synchronises range input values with their display labels in real time.
- resetForm() — Restores all inputs to default values and hides the results panel.
- calcGrade() — Maps a numeric score to a letter grade and descriptive label.
- buildCharts() — Instantiates all four Chart.js visualisations with appropriate configurations.
- buildProgressBars() — Renders colour-coded HTML/CSS progress bars for five key metrics.
- buildStrengthsWeaknesses() — Filters and sorts dimensions into strength and improvement lists.
- buildActionPlan() — Generates a six-step action plan based on the student's specific metric values.
- buildMetricCards() — Renders four summary metric cards with status-based colour coding.

- fetchAIAnalysis() — Constructs the structured prompt and makes the asynchronous Anthropic API call.
- analysePerformance() — The main entry point coordinating all modules and managing loading state.

Chart instances are stored in a shared object and destroyed before each new render to prevent canvas memory leaks, a critical consideration in single-page applications that re-render visualisations on repeated user interactions [15].

9. Results & Output Analysis

When a student submits their data, EduTrack produces a comprehensive multi-panel results dashboard. The following describes each output component and its analytical significance.

9.1 Score Banner

The score banner displays the student's name, grade, stream, and academic year alongside a conic-gradient circular score indicator showing the overall weighted score and a corresponding letter grade (A+ through F). This provides an immediate, high-level summary of academic standing.

9.2 Data Visualisations

The four Chart.js visualisations collectively provide a 360-degree view of the student's performance. The radar chart reveals the shape of the student's academic profile across all eight dimensions, making it immediately apparent which areas are balanced and which are outliers. The colour-coded bar chart (green ≥75%, orange 50–74%, red <50%) provides rapid categorical assessment. The doughnut chart quantifies the ratio of strong to weak dimensions, and the progress bars offer a clean linear reading of five core metrics.

9.3 AI-Generated Assessment

The Anthropic Claude API consistently produces personalised assessments that directly reference the student's numeric values, identify correlational patterns (e.g., the relationship between high stress scores and lower exam performance), and offer subject-specific advice. The NLP output demonstrates contextual awareness of the student's stated goal and weakest subject, producing recommendations that are more specific and actionable than those possible with rule-based templating systems [13].

9.4 Action Plan

The six-step action plan is dynamically generated by comparing each metric against defined thresholds. Steps related to exam performance, attendance, stress management, study schedule, subject strengthening, and milestone setting adapt their content based on the student's specific values, ensuring relevance to each individual's unique profile.

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10. Discussion

EduTrack demonstrates that a meaningful, AI-enhanced academic intelligence tool can be built and deployed without backend infrastructure. The combination of a weighted quantitative score, multi-type data visualisation, and LLM-generated qualitative narrative addresses the limitations of both purely quantitative (grade-only) and purely qualitative (teacher remarks) feedback systems.

The decision to use the Anthropic Claude API for narrative generation, rather than a rule-based template system, proved significant. The LLM's ability to identify non-obvious correlations between metrics — for example, noting how high extracurricular activity combined with low study hours and high stress suggests an over-commitment pattern — produces insights that a static system could not generate [10].

From an educational technology perspective, EduTrack aligns with the learning analytics framework described by Baker and Siemens (2014), prioritising actionable student-facing insights over institutional reporting [8]. The system's accessibility as a static webpage also makes it viable for resource-constrained educational settings where institutional platforms are unavailable.

11. Limitations & Future Scope

11.1 Current Limitations

- Data Persistence: The system does not store student data between sessions. All inputs are lost on page refresh, preventing longitudinal tracking.
- Authentication: There is no user login system, meaning data is not tied to a specific student identity.
- Browser Dependency: The application requires a modern browser with JavaScript enabled and internet access for the Anthropic API call.
- Self-Reported Data: Several metrics (participation, stress, study hours) rely on honest self-assessment, which may introduce subjectivity bias.
- Single-Session Analysis: The system analyses a snapshot rather than a trend, limiting its ability to detect improvement or decline over time.

11.2 Future Scope

- Backend Integration: Implementing a Node.js or Python backend with a database (PostgreSQL or MongoDB) to enable persistent student records and historical trend analysis.
- Student Authentication: Adding a login system to associate data with individual student profiles across multiple sessions.

- Longitudinal Dashboard: Building a trend visualisation panel showing performance changes across weeks or terms.
- Teacher Portal: A separate dashboard for teachers to view aggregated class-level performance analytics.
- Mobile Application: Converting the web application to a cross-platform mobile app using React Native or Flutter.
- Automated Data Integration: API integration with institutional Learning Management Systems (e.g., Moodle, Canvas) to auto-populate metrics rather than relying on manual input.

12. Conclusion

This paper presented EduTrack, a browser-based student performance tracking and enhancement system that integrates data science visualisation with NLP-powered AI assessment. By analysing eight academically validated performance dimensions through a weighted scoring algorithm, rendering multi-type interactive visualisations using Chart.js, and leveraging the Anthropic Claude large language model to generate personalised written assessments, EduTrack delivers a richer and more actionable picture of student academic standing than conventional grade-based reporting systems.

The system demonstrates that meaningful AI-assisted academic guidance does not require complex institutional infrastructure — a carefully designed static web application, powered by a modern LLM API, can deliver personalised, multi-dimensional insights accessible to any student with a browser. As AI technology continues to mature, systems like EduTrack represent a promising direction for democratising personalised education and helping every student chart a clearer path to their full academic potential [1] [6].

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