Behaviour Based Cognitive Drift Detection Framework for Classroom Learning Environment

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ABSTRACT

The gap between student engagement and academic performance remains a critical yet often invisible problem in modern classrooms. Traditional assessment methods, reliant on periodic examinations, fail to capture the gradual process of student disengagement, termed 'cognitive drift'. This paper presents a novel real-time framework for detecting cognitive drift by continuously analyzing behavioural data within a classroom learning environment. The system monitors key indicators such as quiz score trends, response time variability, and study session consistency. A weighted mathematical model computes a quantifiable Drift Score (D), used to classify students into three risk categories: Normal, Moderate Drift, and High Drift. Implemented as a full-stack web application using the LAMP stack (Linux, Apache, MySQL, PHP), the framework includes dedicated modules for students, teachers, and administrators. This work details the system architecture, database schema, drift detection logic, and demonstrates the framework's effectiveness through a working example, enabling proactive, data-driven educational interventions.

Keywords—Cognitive Drift, Student Disengagement, Behavioural Analytics, Learning Analytics, Educational Technology, Real-time Monitoring, PHP, MySQL

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I. INTRODUCTION

The primary objective of any educational system is to facilitate effective learning. However, a significant challenge persists in identifying students who are gradually disengaging from the learning process before it severely impacts their academic outcomes. This gradual disengagement, which we define as **cognitive drift**, is characterized by a subtle but progressive decline in a student's mental engagement, focus, and active participation in their studies. It is a precursor to poor performance, but unlike the final exam score, it is a process that unfolds over time.

Traditional academic systems are structurally deficient in detecting cognitive drift. This approach presents two fundamental flaws:

1. **Reactive, Not Proactive:** It only provides feedback after the learning cycle is complete, when the "damage" is done.
2. **Coarse-Grained Analysis:** A single exam score is a lagging indicator. It represents a snapshot of performance on a given day, influenced by many factors, and completely obscures the preceding weeks of potential disengagement.

II. OBJECTIVES

The development of this framework is guided by a set of clear and measurable objectives:

- **Primary Goal:** To design, develop, and validate a real-time, behaviour-based cognitive drift detection system that quantifies student disengagement as a dynamic Drift Score.
- **Secondary Goals:** To facilitate timely and preventive support by identifying students at risk of cognitive disengagement well before performance deterioration becomes evident in summative assessments, thereby enabling educators to implement targeted interventions at the earliest possible stage.

III. SYSTEM OVERVIEW

The proposed framework is a multi-user web application with three primary modules working in concert.

A. Student Module

This is the primary data collection point. Students log in to:

1. View and select subjects to study.
2. Start and end study sessions, during which a timer tracks their focused study time.
3. Attempt subject-specific quizzes with a built-in timer.

B. Admin Module

This module is for system configuration and user management. An administrator can:

1. Add and manage student records (name, register number, department).
2. Add and manage subjects.
3. Create new quizzes by adding multiple questions, options, and correct answers for any subject.
4. Assign subjects to students, defining their curriculum.

C. Drift Analysis Engine

This is the core computational logic. It runs in the background, triggered by student activities. It:

1. Collects behaviour metrics from the database (quiz scores, response times, study times).
2. Computes a baseline of "normal" behaviour for each student.
3. Applies a weighted scoring formula to calculate a real-time Drift Score.
4. Stores the Drift Score and risk category in the database for display on the teacher dashboard.

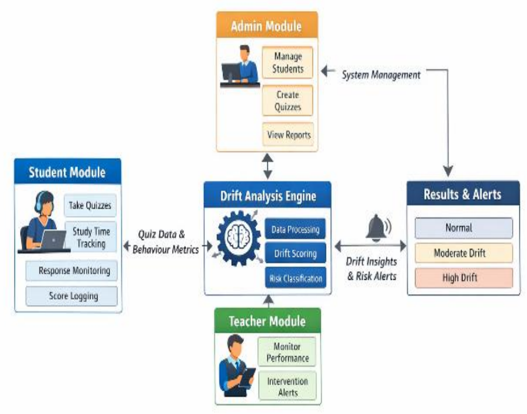


Figure 1: System Workflow Diagram

IV. SYSTEM ARCHITECTURE

The system follows a classic three-tier architecture, promoting separation of concerns, scalability, and maintainability.

A. Presentation Layer (Frontend)

This is the user interface built with HTML5, CSS3, and JavaScript. It is responsible for rendering dynamic content, handling user interactions (like button clicks), and making asynchronous requests (AJAX) to the backend. The interface adapts to the role of the logged-in user (student, teacher, admin).

B. Application Layer (Backend)

This layer, written in PHP, contains the core business logic. It acts as a mediator between the frontend and the database. It handles session management, processes form submissions, executes the drift detection algorithm, and serves data to the frontend in JSON format for dynamic updates.

C. Database Layer

This layer, powered by MySQL, is responsible for persistent data storage. It maintains all tables for users, students, subjects, quizzes, attempts, and behaviour logs.

D. Data Flow Explanation

1. A student starts a quiz via the frontend.
2. An AJAX request is sent to a backend PHP endpoint (e.g., submit_quiz.php).
3. The PHP script validates the session, processes the answers, and stores the attempt data (score, time taken) in the MySQL database.
4. Upon successful storage, the PHP script may also trigger a lightweight function to update the student's behavioural summary.
5. The teacher's dashboard, when loaded, queries the database for all student behaviour data, processes it, and displays it in a formatted table.
6. The admin, when adding a student, fills a form which POSTs data to add_student.php, which in turn creates new records in the student and user tables.

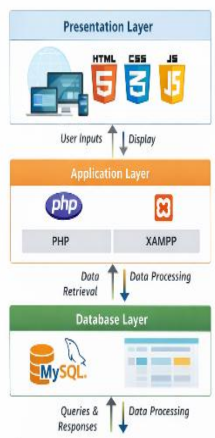


Figure 2: Three-Tier Architecture Diagram

V. TECHNOLOGY STACK

The framework is built on a robust and widely-accessible technology stack, making it ideal for deployment in resource-constrained educational settings like college labs.

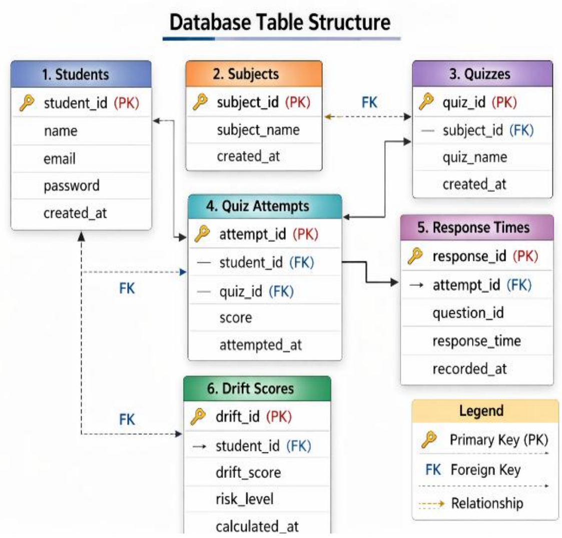
Table 2: Technology Stack Components

Component	Technology	Purpose
Environment	XAMPP	Integrated development and deployment platform
Web Server	Apache	Handles HTTP requests and serves web pages
Backend	PHP	Server-side business logic and data processing
Database	MySQL	Persistent data storage and management
Frontend	HTML5/CSS3	Structure and styling of user interface
Client-side Logic	JavaScript	Interactivity and asynchronous requests
Version Control	Git/GitHub	Source code management and collaboration

VI. DATABASE DESIGN

The database schema is normalized to ensure data integrity and reduce redundancy. The core tables and their relationships are as follows:

A. Table Structure



B. Relationships

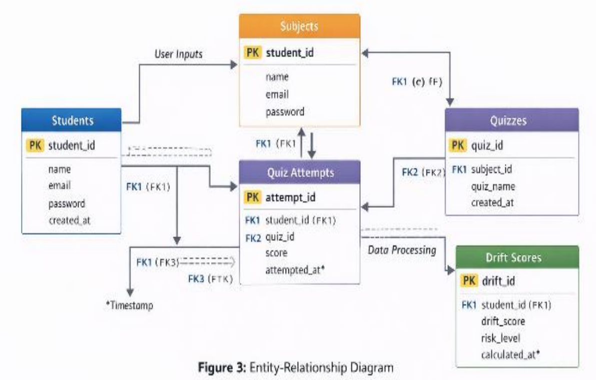


Figure 3: Entity-Relationship Diagram

VII. BEHAVIOURAL METRICS COLLECTED

The framework collects a multi-dimensional set of behavioural metrics to construct a holistic view of student engagement.

A. Quiz Score Trend (S)

This is not a single score but the slope of a student's quiz scores over time. A consistently declining trend is a strong indicator of drift, even if individual scores remain average.

B. Study/Revision Time (P)

The total duration of focused study sessions, as recorded by the system's timer, per subject. A decline in this metric indicates waning effort and engagement.

C. Participation Consistency

This looks at the regularity of quiz attempts. A student who previously attempted all available quizzes but now starts skipping them is showing signs of drift.

D. Attempt Frequency

The number of quiz attempts per week. A sudden drop in attempt frequency can signal a loss of interest.

VIII. DRIFT DETECTION LOGIC

The core intelligence of the system lies in its drift detection logic, which transforms raw metrics into an actionable score.

A. Baseline Calculation

The system first establishes a baseline of "normal" behaviour for each student. This baseline is calculated from their first N interactions (e.g., first 3 quiz attempts and first 2 hours of study time) during a defined "settling period" at the start of the academic term.

B. Weighted Scoring Formula

A student's current behaviour is compared against their baseline to derive a composite Drift Score (D). The formula is a weighted sum of normalized deviations:

$$D = w_1 \cdot S_{dev} + w_2 \cdot R_{dev} + w_3 \cdot P_{dev}$$

C. Threshold-Based Classification

The resulting Drift Score (D) is normalized to a scale of 0 to 100. This score is used to classify the student into a risk category:

Table 5: Risk Classification Thresholds

Drift Score Range	Risk Category	Teacher Action Required
0 – 30	Normal	Regular monitoring
31 – 60	Moderate Drift	Observe and check-in
61 – 100	High Drift	Immediate intervention

IX. IMPLEMENTATION PROCESS

The system was developed in a phased, iterative manner:

Phase 1: Database Schema & Login System

Phase 2: Core Student Functionality

Phase 3: Quiz Engine

Phase 4: Timer Logic

Phase 5: Drift Score Update

Phase 6: Dashboard Visualization

Table 6: Implementation Timeline

Phase	Duration	Key Deliverables
1	Week 1	Database schema, login system
2	Week 2	Student dashboard, study timer
3	Week 3	Quiz engine, question bank
4	Week 4	Timer integration, session tracking
5	Week 5	Score calculation, attempt logging
6	Week 6	Drift algorithm, batch processing
7	Week 7	Teacher/admin dashboards
8	Week 8	Testing, debugging, deployment

X. SAMPLE WORKING EXAMPLE

To illustrate the system's functionality, consider a student named "Bob" over an 8-week period in a "Mathematics" course.

A. Baseline Period (Weeks 1-2)

Bob actively uses the system. He takes 3 quizzes, scoring an average of 85%. His average response time is 45 seconds per question, and he studies for an average of 120 minutes per week. This forms his baseline.

B. Early Drift Detection (Weeks 3-4)

Bob's quiz scores start to dip to an average of 78% (S_dev increases). His response time becomes erratic, averaging 55 seconds (R_dev increases). His study time drops to 90 minutes per week (P_dev increases).

C. Progressive Drift (Weeks 5-6)

The trend worsens. Bob's average score falls to 65%. His response time becomes very fast, averaging 30 seconds (suggesting guessing). His study time plummets to 45 minutes.

D. Post-Intervention Recovery (Weeks 7-8)

Following a conversation with his teacher and counselor, Bob's engagement improves. His scores recover to 80%, his response time stabilizes to 48 seconds, and his study time increases to 100 minutes.

XI. ADVANTAGES OF THE SYSTEM

The behaviour-based cognitive drift detection framework offers several key advantages over conventional classroom monitoring approaches:

1. **Early Identification of At-Risk Students:** The system enables proactive detection of cognitive disengagement weeks or even months before traditional summative assessments reveal performance decline, allowing timely pedagogical interventions.

2. **Timely and Targeted Teacher Support:** By delivering objective, data-driven alerts, the system empowers educators to implement precise, individualized interventions at the moment drift is detected, enhancing responsiveness and instructional effectiveness.

3. **Objective and Quantifiable Measurement:** The framework introduces a standardized, quantifiable metric of disengagement based on observable behavioural indicators, reducing reliance on subjective teacher judgment and improving reliability and comparability across classrooms.

4. **High Scalability:** Capable of simultaneously monitoring large cohorts of students (hundreds in a single deployment), the system is well-suited for modern large-scale and hybrid classroom environments.

XII. LIMITATIONS

Despite its potential, the system has some limitations:

1. **Proxy-Based Measurement of Engagement:** The framework infers cognitive engagement through observable behavioural proxies (eye gaze, head pose, posture, facial expression, etc.) rather than directly

measuring internal cognitive states.

2. **Technical Infrastructure Requirements**: Effective deployment requires reliable hardware (cameras, computing devices) and stable internet connectivity in every classroom.

3. **Privacy and Ethical Concerns**: Continuous monitoring of student behaviour using cameras and sensors raises significant privacy issues. Even with anonymization and on-device processing, the perception of surveillance may affect student comfort, trust, and classroom dynamics.

XIII. FUTURE ENHANCEMENTS

The framework is designed with extensibility in mind. Future work will focus on:

A. Machine Learning Integration

Replacing the heuristic threshold model with a supervised machine learning classifier (e.g., Random Forest, SVM) trained on historical student data to predict failure with higher accuracy.

B. Predictive Analytics

Developing a model that not only detects current drift but also predicts the likelihood of a student failing a future exam based on their current drift trajectory.

C. Real-Time Notification System

Implementing an automated notification system (email, SMS, in-app) to alert teachers, counselors, and students themselves when a drift score crosses a critical threshold.

XIV. CONCLUSION

This paper presented a complete, deployable framework for real-time cognitive drift detection using behavioural data in classroom environments. By shifting from reactive marks-based evaluation to proactive engagement-based monitoring, the system empowers educators with actionable insights. Future work will focus on adaptive thresholds, multimodal sensor integration, and large-scale real-world validation.

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