# Innovative Learning System

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## Abstract

It is imperative that virtual education become more customised and flexible. The study suggests an adaptive multiple-choice question test system that instantly adjusts to feedback on a student's emotional state as they are learning. Test questions are correlated with cognitive levels. Emotions such as confidence or perplexity might be considered affective states. After determining the learner's affective state, the system modifies the remaining test questions in the series to reflect that affective state. Confident learners will receive more challenging questions, while confused learners will receive easier ones. This procedure will persist for the educational task. Test system adapts as a result.

**Keywords: Adaptive MCQ, Affective state, Fuzzy logic, Linear regression, Affective Learning system.**

## Introduction

In the rapidly evolving landscape of education, virtual learning systems have emerged as indispensable tools, especially in contemporary times where access to traditional classrooms may be restricted. These systems play a pivotal role in delivering educational content to learners, transcending geographical boundaries. While these virtual learning platforms have streamlined the dissemination of information, a critical aspect often overlooked is the diverse cognitive and emotional states exhibited by learners during their educational journey. Traditional virtual learning systems predominantly rely on static assessments, frequently employing Multiple Choice Questions (MCQs) to evaluate learner comprehension. However, these assessments often fail to capture the nuanced spectrum of learner emotions and cognitive states. The dichotomy between a learner confidently mastering a concept and grappling with confusion remains unaddressed.

The MCQ exam design incorporates behavioural factors of the learner in addition to answer correctness.

1. Option modifications (the number of times a learner modifies an option before deciding on an answer) is one of the supplementary behavioural characteristics.
2. The amount of time needed to complete a task (various cognitive level questions)
3. The amount of time needed to complete the entire test (the portion of the test when questions come from different cognitive levels)

The following phases comprise the adaptive test design that the authors of this research propose:

1. First MCQ test generation rationale based on Bloom's taxonomy's cognitive level
2. Determining the learner's affective state based on how well they performed on a fuzzy scale in the given multiple-choice question test.
3. Create a new test with additional questions at a higher cognitive level if affective state is confidence.
4. Create a new test with more questions at a lower cognitive level if the affective state is

confusion.
5. Continue from steps 2 through 4 until the student has confidence in the subject.

# Motivation

Developing a Innovative Learning System is an incredible journey where you have the opportunity to unlock the joy of learning, one question at a time. Imagine transforming curiosity into knowledge with every tap, creating a world where learning is both fun and engaging. By empowering minds through interactive education, you're challenging intellects and inspiring minds across the globe. ILS will bring the excitement of discovery to every user, making education accessible, engaging, and enjoyable. Each quiz you create will be a step towards mastery, turning learning into an exciting adventure. In your hands, this ILS becomes a gateway to endless learning adventures, where fun meets knowledge and every answer counts.

## Literature Survey

[1]"Adaptive MCQ Test Generation Based on Affective State Feedback" (Kelkar & Bakal, 2020): This paper explores the use of affective state feedback in generating adaptive multiple-choice question (MCQ) tests. It discusses how AI techniques can be employed to tailor test questions based on learners' emotional states, aiming to enhance learning outcomes. [2]"Artificial Intelligence-Enabled Adaptive Learning Systems: A Review" (Smith & Patel, 2020): This review paper provides an overview of AIpowered adaptive learning systems. It likely covers various AI techniques used in educational settings, highlighting their impact on personalized learning experiences and educational outcomes. [3]"Enhancing Adaptive Learning Using AI-Based Question Selection Algorithms" (Gupta & Sharma, 2021): Focusing on AI-based question selection algorithms, this paper likely discusses the methodologies and algorithms employed to enhance adaptive learning. It might explore how these algorithms aid in customizing learning content to suit individual learner needs. [4]"Integration of AI in Educational Assessment: A Systematic Literature Review" (Chen & Wang, 2021): This systematic literature review likely covers the integration of AI in educational assessment. It may discuss various AI techniques used for assessment purposes, such as automated grading, personalized feedback, or adaptive testing. [5]"Adaptive Learning Systems: An Overview of AI-Powered Techniques" (Kim & Lee, 2022): Providing an overview of AI-powered adaptive learning systems, this paper might delve into different AI techniques applied in adaptive learning environments, including personalized content delivery, intelligent tutoring systems, and adaptive assessment.[6]"AI-Driven Personalized Learning: A Comparative Study of Approaches" (Zhang & Liu, 2022): This comparative study likely evaluates and compares different approaches to AI-driven personalized learning. It might discuss the effectiveness of various AI-based strategies in catering to diverse learning styles and needs.[7]"Adaptive Learning Algorithms using Machine Learning for MCQ Generation" (Rahman & Das, 2023): Focusing on adaptive learning algorithms for MCQ generation, this paper could explore how machine learning techniques are employed to create tailored MCQs, aiming to improve learning efficiency.[8]"Implementing AI-Based Adaptive Testing in Educational Environments" (Lee & Wu, 2023): This paper may discuss the implementation of AIbased adaptive testing in educational settings. It might cover practical considerations, challenges, and benefits associated with deploying such testing systems.

# Methodology

## 1] Analysis Model

The analysis model presented evaluates a learner's affective state by considering correctness of answers (P1), number of option changes (P2), and time taken per question (P3) in a multiple-choice question (MCQ) test. Utilizing a linear regression equation, the model computes a fuzzy value, 'A,' ranging from 0 to 1, with 1 indicating confidence and 0 indicating confusion. The coefficients (a, b, c) are derived through training on MCQ tests, and the model is applied to subsequent tests to generate 'A' values for each question. Cumulatively, these values provide a topic-wise measure of the learner's affective state, aiding educators in understanding and addressing areas of confusion or confidence based on the learner's performance.

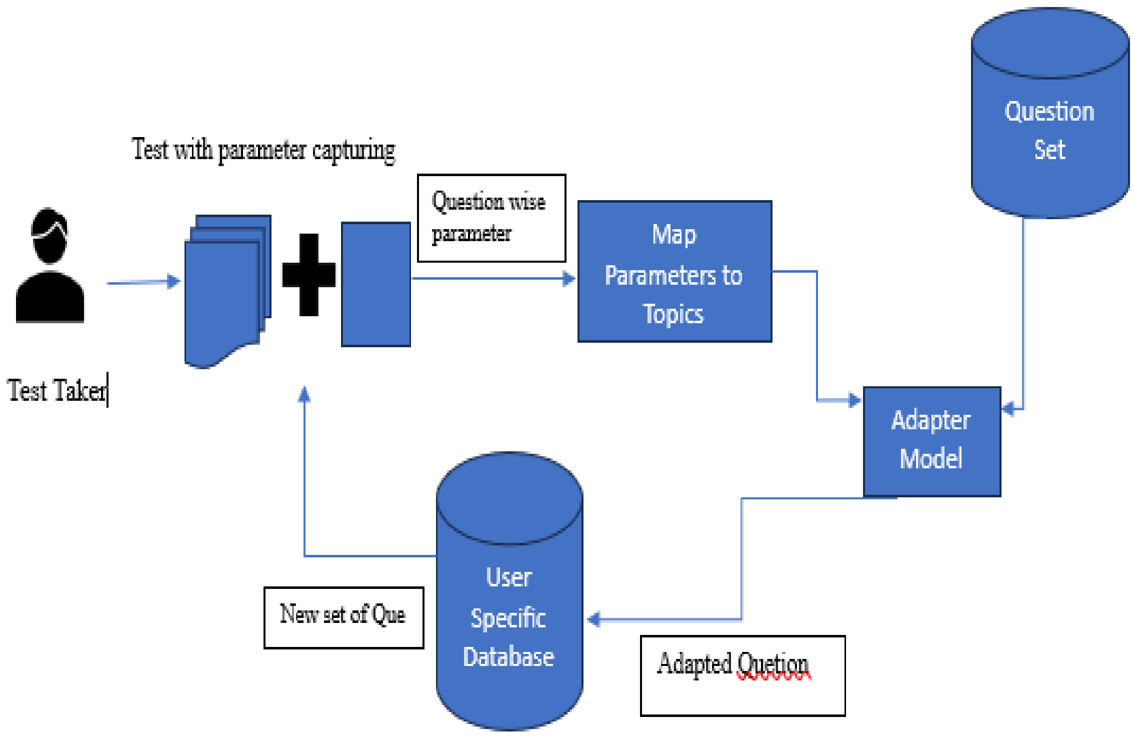



Fig.1 Model Diagram

## 2] System Implementation Plan

Creating a system implementation plan for a water bottle distributor management system using web technology involves a systematic approach to ensure a successful and smooth deployment. Here's a structured plan to guide you through the implementation process:

1. Data Collection: Gather historical data on learner performance in MCQ tests, including correctness of answers, number of option changes, and time taken per question.
2. Model Training: Derive coefficients (a, b, c) for the linear regression equation using a training dataset. Establish the class values for P1, P2, and P3 based on the provided criteria.

3. Model Integration: Implement the linear regression model in the system to compute ’A’ values for each question during subsequent MCQ tests.
4. Parameter Monitoring: Continuously monitor and update the model as new learner performance data becomes available, ensuring the model remains reflective of learner behavior.
5. Testing and Validation: Validate the model by applying it to new MCQ tests and comparing predicted ’A’ values with actual learner outcomes.
6. User Interface Design: Develop a user-friendly interface for educators to input MCQ test results and receive cumulative ’A’ values for each topic.
7. Integration with Educational Systems: Integrate the affective state analysis system with existing educational platforms for seamless implementation and data exchange.
8. Feedback Mechanism: Establish a feedback mechanism for educators to provide insights on the accuracy of the affective state predictions and make necessary adjustments to the model.
9. Continuous Improvement: Regularly assess the system’s performance, gather user feedback, and make enhancements to improve the accuracy and relevance of affective state predictions.

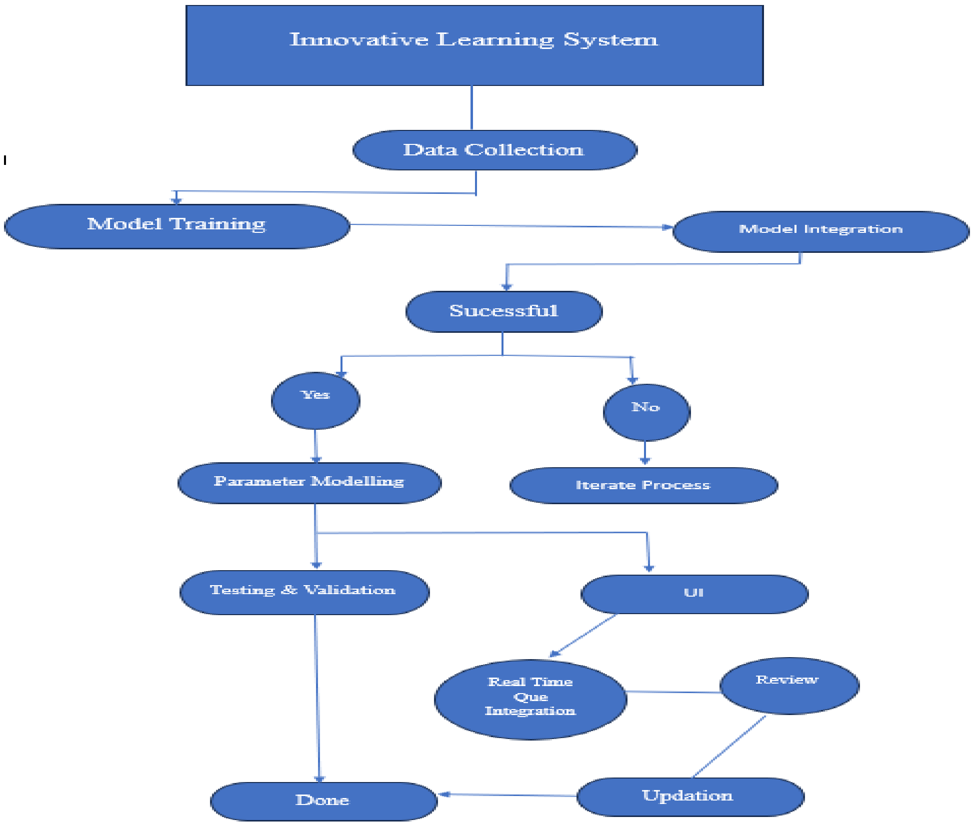



Fig. 2 Project Flowchart

## 3]Data Flow Diagram

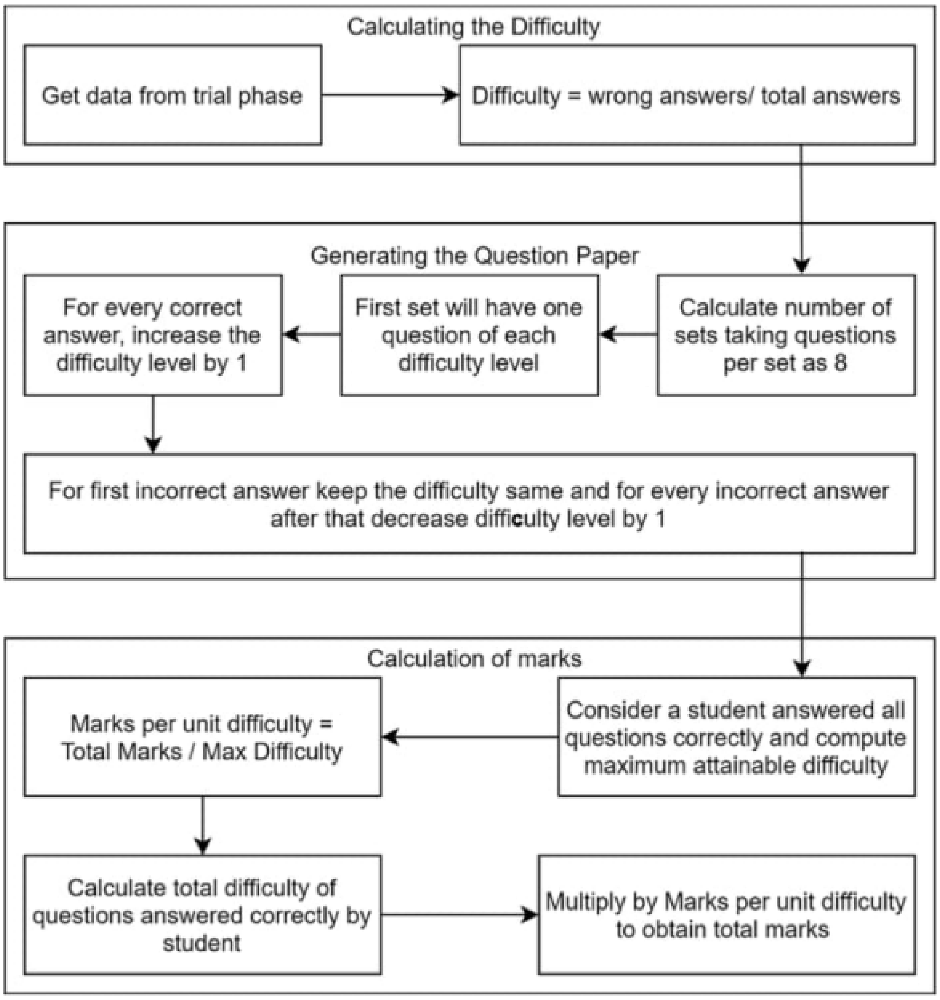



Fig. 3 Data Flow Diagram

## 4] Model Implementation

### 2. Decision Tree Training

For each tree $T_i$, at each node:

1. **Feature Subset Selection:**
    - Randomly select a subset of features $F \subset \{P_1, P_2, P_3, \text{cognitive ability}\}$.
2. **Node Splitting:**
    - For each feature $f \in F$ and for each possible split value $s$, compute the split that minimizes the variance:

$$\text{Variance Reduction} = \text{Var}(D) - \left(\frac{n_L}{n}\text{Var}(D_L) + \frac{n_R}{n}\text{Var}(D_R)\right)$$

    where:

    - $\text{Var}(D)$ is the variance of the target variable in the parent node.
    - $D_L$ and $D_R$ are the left and right child nodes created by the split.
    - $n$, $n_L$, and $n_R$ are the number of samples in the parent, left child, and right child nodes, respectively.
3. **Recursive Splitting:**

### 3. Prediction Aggregation

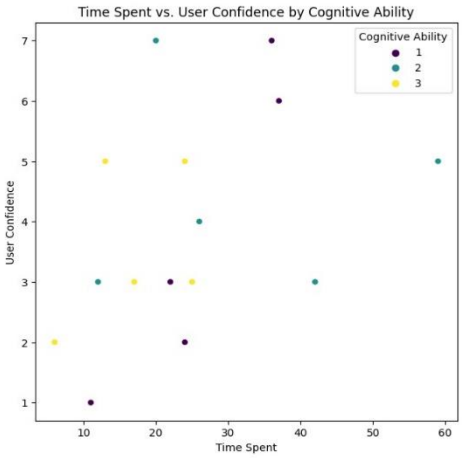
After all trees are trained, make predictions by averaging the outputs of all trees:

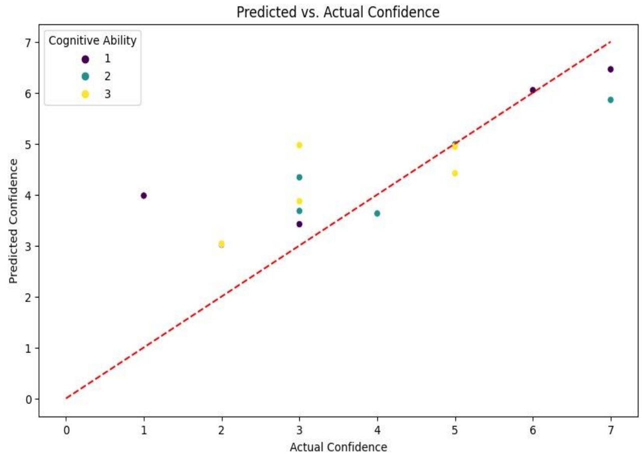
$$\hat{y} = \frac{1}{M}\sum_{i=1}^{M} T_i(X)$$

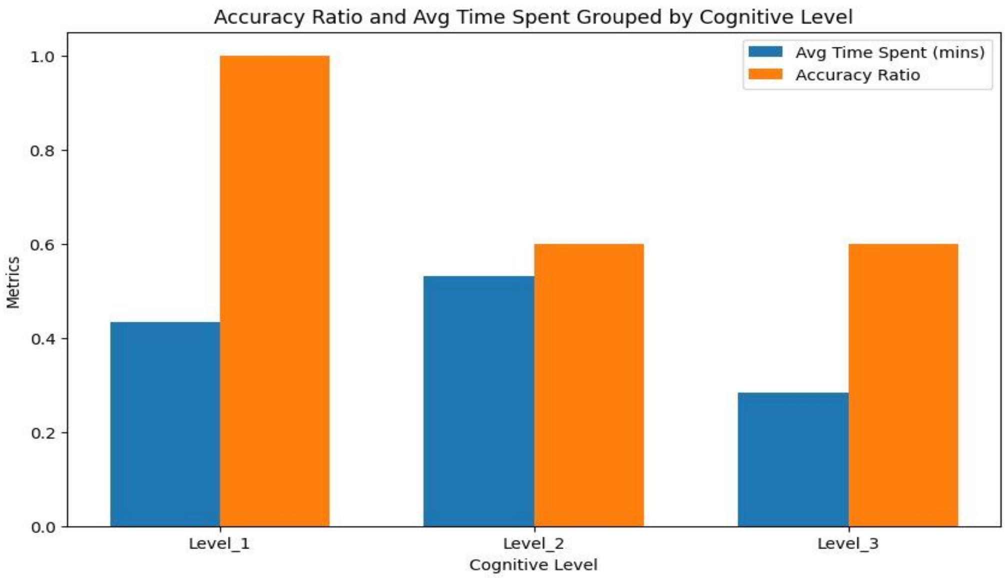
where:

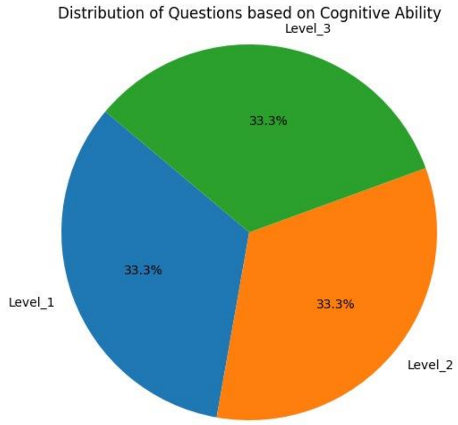
- $\hat{y}$ is the predicted target variable (user confidence).
- $M$ is the number of trees in the forest.
- $T_i(X)$ is the prediction of the $i$-th tree for the input $X$.

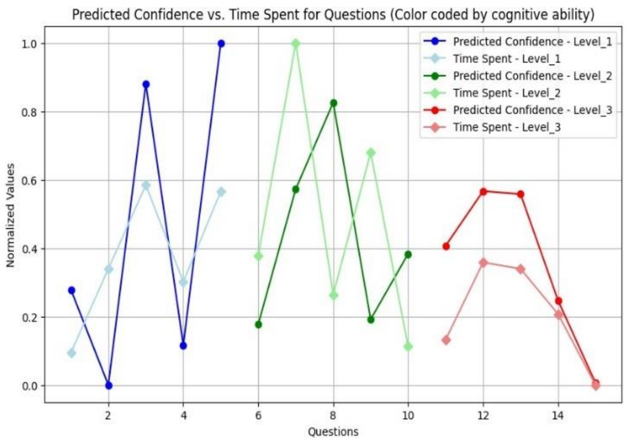
# 4] Resulting Visuals






## Conclusion

In summary, this model represents a pioneering approach to educational assessment, delving beyond traditional metrics by integrating the nuanced dimensions of learner confidence and confusion. By capturing the intricacies of correctness, option changes, and time per question, the project aspires to create a more comprehensive understanding of the learner's emotional and cognitive states during assessments. The envisaged advantages of the project extend beyond the educational landscape, promising to be a transformative force in adaptive learning systems. The system's ability to dynamically adjust content based on individual affective states opens avenues for personalized learning experiences, presenting a paradigm shift in how education is tailored to the unique needs of each learner. While the project showcases promising prospects, it is essential to acknowledge its inherent challenges. These challenges, however, pave the way for innovative solutions and improvements that can propel the project towards its full potential.

## Future Work

In the realm of future work, this project opens avenues for refinement and expansion. Prospective endeavors could involve leveraging advanced machine learning techniques for more precise affective state analysis, potentially incorporating multimodal data sources like video or biometrics. Longitudinal studies may track changes in learners' affective states over time, providing insights into the effectiveness of interventions. Seamless integration with Learning Management Systems (LMS) and the exploration of adaptive feedback mechanisms are also promising directions. Addressing privacy and ethical considerations, adapting the project for online learning, and investigating cross-cultural validity are critical areas for further exploration. Real-time intervention strategies and a quantitative-qualitative hybrid approach could further enhance the project's impact, revolutionizing our understanding and support for learners in diverse educational contexts.

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