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Learning Behaviour Analysis and Visualization System

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Abstract: *The Learning Behaviour Analysis and Visualization System aims to enhance the personalization of e-learning by identifying and analysing individual learning styles. Leveraging the Felder-Silverman Learning Styles Model, the system classifies learners based on psychological self-assessments. Hybrid filtering techniques and intuitionist fuzzy logic are used to predict learner preferences and handle uncertainty in responses. A Learner Characteristic Model captures interpersonal traits, while pattern analysis evaluates efficiency. Logistic regression is employed to forecast learner performance using historical data. The system visually represents learning behaviours to aid both learners and instructors. Additionally, a recommendation engine suggests suitable educational resources. This approach promotes adaptive learning, improves engagement, and supports data-driven educational strategies*

Keywords: Learning Behaviour, Fuzzy Logic, Hybrid Filtering, Visualization, Learner Characteristic Model, Adaptive Learning

I. INTRODUCTION

In today's digital learning environment, understanding individual learner behavior is essential for delivering effective and engaging educational experiences. Traditional E-learning systems often lack adaptability and fail to address diverse learning preferences. This limitation reduces course effectiveness and student motivation. The Learning Behaviour Analysis and Visualization System addresses this gap by identifying learning styles through psychological profiling and data analysis. By applying predictive analytics and fuzzy logic, the system classifies learners and visualizes their styles. It also evaluates performance using machine learning techniques and offers personalized recommendations. This data-driven approach enhances the learning experience, supports informed teaching strategies, and fosters academic growth.

II. LITERATURE SURVEY

1. A PERSONALIZED ADAPTIVE LEARNING FRAMEWORK BASED ON REINFORCEMENT LEARNING, By IEEE Access, 2023

This paper introduces a reinforcement learning-based framework for recommending personalized learning paths. It highlights the importance of learner profiling and sequential learning recommendations based on historical data. However, it lacks explicit consideration of learners' cognitive styles and emotional factors, which are key to effective personalization.

2. AN INTELLIGENT RECOMMENDATION SYSTEM FOR E-LEARNING BASED ON LEARNING STYLES, International Journal of Emerging Technologies in Learning, 2021

This study uses Felder-Silverman Learning Style Model (FSLSM) to classify learners and recommend suitable learning content. Although it effectively adapts learning resources to styles, it focuses mainly on static preferences and lacks dynamic performance tracking.

3. PREDICTIVE ANALYTICS FOR STUDENT PERFORMANCE BASED ON LEARNING ,Computers in Human Behavior, 2020

This research applies machine learning techniques such as logistic regression and decision trees to predict student performance. It emphasizes behavioral data such as quiz attempts, session duration, and content interaction, yet does not integrate psychological self-assessment data.

4. LEARNING STYLE DETECTION USING QUESTIONNAIRE AND NEURAL NETWORK TECHNIQUES, Education and Information Technologies, 2019

This work combines traditional questionnaires with neural network classifiers to detect learning styles. While it improves accuracy in classification, it does not provide real-time performance feedback or visualizations for educators.

5. VISUALIZATION OF STUDENT LEARNING PATHS FOR PERFORMANCE ENHANCEMENT, IEEE Transactions on Learning Technologies, 2018

This paper focuses on visual analytics to represent student progress and learning trajectories. Though effective for instructors, it lacks integration with predictive analytics models and learner self-assessment mechanisms.

III. PROPOSED SYSTEM

- Existing e-learning systems primarily focus on content delivery without adapting to individual learning styles.
- Most current platforms lack intelligent behavior analysis, leading to a one-size-fits-all approach that reduces engagement and effectiveness.
- Prediction of learner behavior and performance is often manual or based on a single course or fixed pattern, which decreases accuracy and scalability.
- The classification of learners is often static and doesn't reflect dynamic changes in performance or preferences.

Demerits

- Learner style identification is manual and not scalable.
- Existing systems lack integration of behavioral and psychological inputs.
- Current prediction models do not account for interpersonal learning traits.
- Visual representation of learner progress is limited or unavailable.
- The systems do not adapt to learner behavior in real time.

Proposed work

This project proposes a Learning Behaviour Analysis and Visualization System aimed at identifying learner styles through psychological self-assessment. It utilizes a hybrid filtering approach combined with an intuitionist fuzzy model to predict various learner characteristics. To forecast learner performance, the system employs logistic regression based on quiz scores. Additionally, learning styles and performance outcomes are visualized to enhance comprehension and insight. To further support individual learning needs, a personalized recommender system is integrated to suggest suitable learning resources tailored to each learner.

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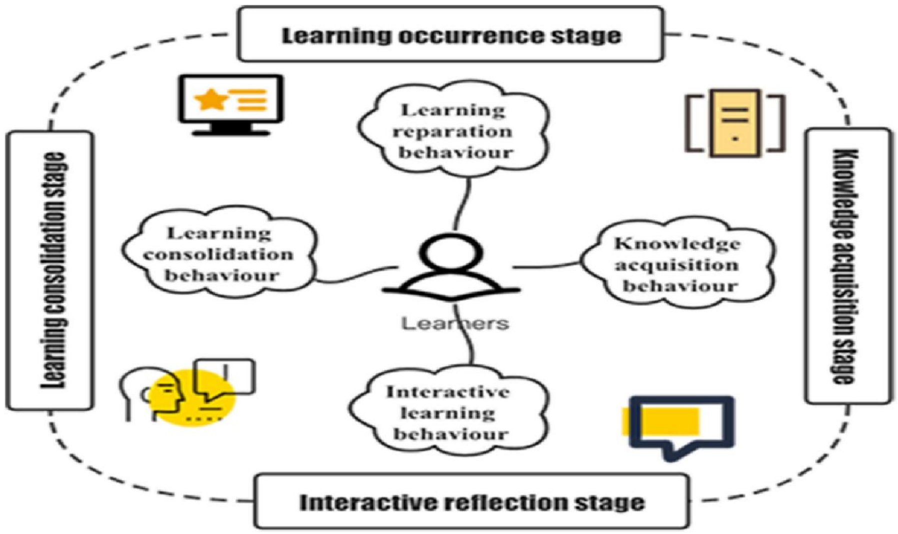

IV. SYSTEM ARCHITECTURE

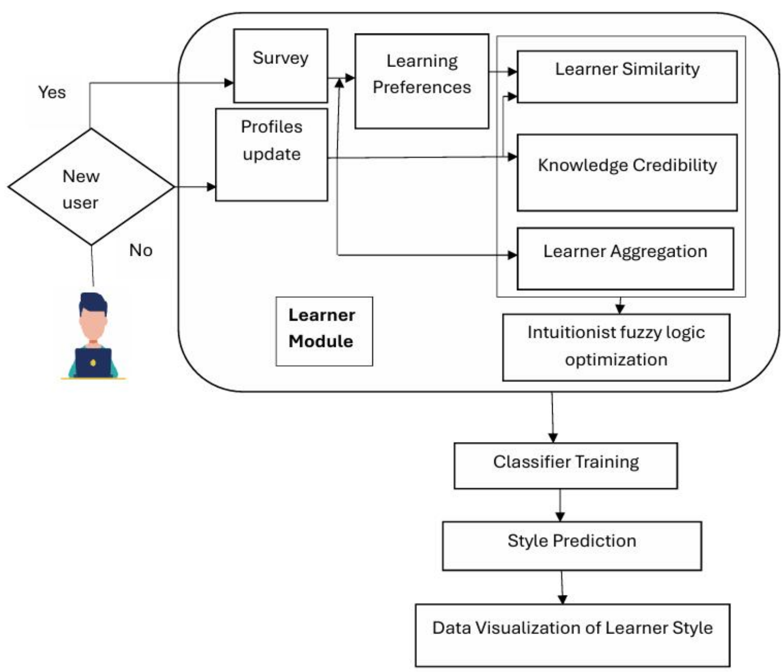

Figure 1: System Architecture

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System Architecture Overview

1. Learner Input Interface: Captures responses from learners through psychological self-assessment questionnaires.
2. Preprocessing Module: Performs data cleaning, stop-word removal, tokenization, and transforms raw input into structured format.
3. Hybrid Filtering Engine: Combines content-based and collaborative filtering techniques to develop the Learner Characteristic Model (LCM).
4. Intuitionist Fuzzy Logic Module: Manages uncertainty and imprecision in learner data to improve model accuracy.
5. Performance Prediction Engine: Applies logistic regression on learner quiz scores to forecast academic performance.
6. Learner Style Identification Module: Analyzes behavioral data to classify and identify dominant learning styles.
7. Visualization Dashboard: Presents insights into learner styles and performance using interactive charts and visual summaries.
8. Recommendation System: Delivers personalized learning resources aligned with each learner's preferences and predicted outcomes.
9. Modular System Integration: Ensures seamless interaction between components in a sequential, dynamic processing flow.
10. Real-Time Adaptation: Enables continuous learning model updates for accurate prediction and adaptive personalization.
11. Outcome: Provides a scalable, intelligent framework to enhance e-learning effectiveness through behavioral analysis and tailored resource delivery.

V. ALGORITHMS

1. LOGISTIC REGRESSION

Used for predicting learner performance based on features like quiz scores and behavioral data. It models the probability of a learner succeeding or failing in tasks based on previous performance metrics.

2. HYBRID FILTERING ALGORITHM

Combines content-based filtering (recommending based on the learner's own data) and collaborative filtering (recommending based on similarities with other learners) to build a robust Learner Characteristic Model (LCM).

3. INTUITIONIST FUZZY LOGIC

Used to handle uncertainty and vagueness in the learner's self-assessment responses. It considers three factors: truth, falsity, and hesitation, which improves the precision of learning style detection.

4. FELDER-SILVERMAN LEARNING STYLE MODEL (FSLSM)

A psychological framework—not an algorithm—but central to the project. It classifies learners into categories like Active–Reflective, Sensing–Intuitive, Visual–Verbal, and Sequential Global, based on responses to a questionnaire.

VI. MODULES

1. LEARNER INPUT MODULE

This module presents a set of psychological self-assessment questions to the learner. The answers are used to analyze learner preferences based on the Felder-Silverman Learning Style Model. The data collected is preprocessed and stored for further analysis.

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2. STYLE PREDICTION MODULE

Using the preprocessed input, this module predicts the learning style of each user. It uses a trained dataset and classification logic, applying a hybrid filtering technique to determine if the learner is visual, verbal, sequential, or global. The Intuitionist Fuzzy Logic enhances prediction by handling uncertainty in responses.

3. LEARNING STYLE VISUALIZATION MODULE

Once the learning style is predicted, this module displays the results graphically. Charts and graphs are generated to show the distribution and dominance of learning traits, making it easier for educators and learners to understand the learner's style profile.

4. RECOMMENDATION SYSTEM MODULE

Based on the learner's predicted style, this module provides personalized content suggestions such as articles, videos, or interactive tools. The recommendations are generated using a Learner Characteristic Model (LCM) that matches content to learning preferences.

5. PERFORMANCE PREDICTION MODULE

This module analyzes quiz scores and user interaction patterns using Logistic Regression to forecast the learner's academic performance. It identifies learners at risk and suggests necessary interventions to improve outcomes.

VII. CONCLUSION

The Learning Behaviour Analysis and Visualization System enhances personalized education by accurately identifying individual learner styles. Using psychological assessments aligned with the Felder-Silverman model, the system classifies learning preferences effectively. Intuitionist fuzzy logic manages uncertainty in learner responses, improving the precision of predictions. Logistic regression is applied to forecast academic performance based on quiz scores and behavioral patterns. A hybrid recommendation engine delivers customized learning resources tailored to each learner's style. The visualization component provides clear insights into learning trends, assisting both learners and educators. Overall, the system promotes adaptive, data-driven learning to improve educational outcomes.

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