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"Learn with Me": An AI Adaptive Learning Game for Personalized Child Education

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***Abstract* —** The traditional "one-size-fits-all" approach in educational games often fails to address the diverse learning needs and paces of individual children, leading to disengagement and suboptimal learning outcomes. This paper presents "Learn with Me," a web-based AI adaptive learning game designed to provide personalized educational experiences for children. The system employs **Bayesian Knowledge Tracing (BKT)** , a machine learning technique that models a child's knowledge state by analyzing their response patterns in real-time. Based on this analysis, the game automatically adjusts question difficulty, ensuring that each child is challenged appropriately without becoming frustrated or bored. The system tracks key performance metrics including learning speed, accuracy, and overall progress. "Learn with Me" combines engaging gameplay with intelligent adaptation to make learning interactive, effective, and enjoyable. This paper details the system architecture, AI model implementation, and preliminary testing results, demonstrating the potential of AI-driven adaptive games to revolutionize early childhood education.

1. Introduction

Early childhood education lays the foundation for lifelong learning, cognitive development, and academic success. However, engaging young learners and maintaining their motivation remains a persistent challenge for educators and parents alike. Traditional educational methods often rely on static content delivery, where all children receive the same material regardless of their individual comprehension levels, learning styles, or progress rates.

The emergence of educational technology has introduced new possibilities for making learning more interactive and enjoyable. Among these innovations, educational games—or "serious games"—have gained significant attention for their ability to combine entertainment with learning objectives. However, many of these games suffer from a critical limitation: they lack the intelligence to adapt to individual learners' needs.

1.1 Problem Statement

The challenges that "Learn with Me" addresses can be summarized as follows:

(1) One-Size-Fits-All Content: Traditional educational games and learning platforms provide uniform content and difficulty levels to all children. A child who learns quickly may become bored with repetitive easy questions, while a child who struggles may become frustrated and demotivated by challenging content that is beyond their current capability.

(2) Lack of Real-Time Feedback: Most existing educational games fail to adapt dynamically based on a child's performance. They typically provide only binary feedback—correct or incorrect—without using this information to modify the learning path or difficulty level. This limits the effectiveness of the learning experience.

(3) Limited Monitoring Capabilities: Teachers and parents often find it difficult to continuously monitor each child's learning progress, identify specific areas of difficulty, and intervene appropriately. Without data-driven insights, personalized intervention becomes challenging.

The aim of this research is to understand the various characteristics and objectivies of this systematic review are to:

- To develop an AI-based adaptive learning game for children.
- To provide personalized learning experiences based on each child's performance.
- To automatically adjust difficulty levels using machine learning algorithms.
- To make learning fun and engaging through educational gameplay.
- To improve children's knowledge retention, problem-solving abilities, and critical thinking skills.

1.2 Proposed Solution

To address these challenges, we present "Learn with Me," an AI-powered adaptive learning game designed specifically for children. The system leverages Machine Learning, specifically Bayesian Knowledge Tracing (BKT) , to create a personalized learning environment that:

(1) Adapts in Real-Time: The game dynamically adjusts question difficulty based on the child's performance, ensuring optimal challenge levels.

(2) Provides Personalized Learning: Each child receives questions tailored to their current knowledge state, focusing on areas that need improvement.

(3) Tracks Comprehensive Progress: The system analyzes learning speed, accuracy, response time, and overall performance to build a detailed learning profile.

2. Literature Review

2.1 Adaptive Learning Systems

Adaptive learning systems aim to personalize the educational experience by adjusting content, pace, and difficulty based on individual learner characteristics. *Gaurav and Kadyan (2026)* proposed an AI-based adaptive learning framework for children with Intellectual and Developmental Disabilities (IDD). Their system utilized gesture interaction, behavior monitoring, and mood recognition to dynamically adjust content difficulty and game complexity without requiring intrusive sensors. This work demonstrates the potential of AI to create inclusive and adaptive learning environments for diverse learner populations.

Yang and Li (2025) conducted a comprehensive review of AI-enabled adaptive game-based language learning, examining both theoretical foundations and practical implementations. Their research highlighted the effectiveness of adaptive systems in improving language acquisition outcomes and learner engagement. They emphasized the importance of real-time adaptation based on learner performance data.

2.2 Bayesian Knowledge Tracing in Education

Bayesian Knowledge Tracing (BKT) is a prominent machine learning technique used in intelligent tutoring systems to model student knowledge. *McLaren and Nguyen (2022)* discussed the application of AIED (Artificial Intelligence in Education) in digital learning games, highlighting the effectiveness of knowledge tracing models in predicting student performance and adapting instruction.

Xu (2025) explored game-based adaptive learning in probability education, demonstrating how adaptive systems can improve student understanding of complex mathematical concepts. The research showed that students using adaptive games performed better than those using traditional learning methods.

2.3 Research Gap

While the reviewed literature demonstrates significant progress in AI-driven adaptive learning and educational games, several gaps remain:

- **Limited Application to General Elementary Education:** Most existing research focuses on specific domains (e.g., IDD children, engineering students, language learning) or specific subjects, with limited application to general elementary education.
- **Implementation Complexity:** Many proposed systems require sophisticated hardware or complex setups, limiting their accessibility for widespread educational use.
- **Limited Real-Time Adaptation:** Some systems adapt over extended periods rather than providing real-time difficulty adjustment based on immediate performance.
- **Lack of Web-Based Solutions:** Many adaptive learning games are platform-specific or require installation, limiting accessibility.

3. Methodology

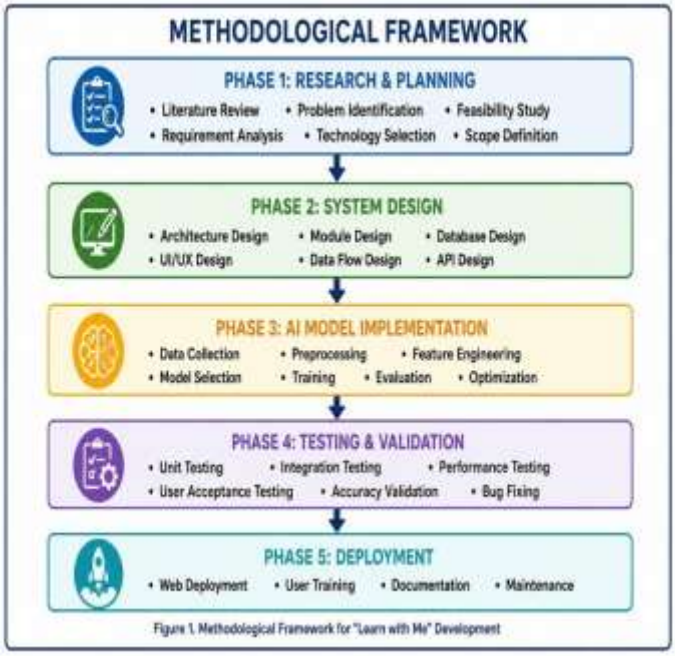


Figure 1. Methodological Framework for "Learn with Me" Development

3.1 Research and Planning Phase

1) *Feasibility Study*

A feasibility assessment was conducted across three dimensions:

- **Technical Feasibility:** Assessment of available technologies (Python, Flask, JavaScript, SQLite) confirmed that all required tools were accessible and well-documented.
- **Operational Feasibility:** Evaluation of the development team's skills and time constraints indicated that the project was achievable within the allocated 2026-27 session.

- **Economic Feasibility:** Open-source technologies were selected to minimize development costs, making the system economically viable.

2) Requirement Analysis

Functional and non-functional requirements were elicited and documented:

Functional Requirements:

- FR1: The system shall present age-appropriate educational questions
- FR2: The system shall automatically adjust difficulty based on student performance
- FR3: The system shall track individual student progress
- FR4: The system shall provide immediate feedback on answers
- FR5: The system shall generate progress reports

Non-Functional Requirements:

- NFR1: Response time shall be less than 2 seconds
- NFR2: The system shall support concurrent users (minimum 50)
- NFR3: The interface shall be intuitive for children aged 6-10
- NFR4: The system shall maintain 99% uptime

3) Technology Selection

Based on the requirements analysis, the following technology stack was selected:

Component	Technology	Rationale
Frontend	HTML5, CSS3, JavaScript	Cross-platform compatibility, no plugins required
Backend Framework	Node.js (JavaScript)	Fast, scalable, event-driven, great for real-time applications
AI Library	Scikit-Learn, NumPy	Comprehensive ML tools, well-documented
Development Environment	Visual Studio Code	Free, feature-rich, supports all technologies

3.2 AI Model Implementation Phase

1) Data Collection

Data for the AI model was collected through:

a) Pilot Testing: 50 students (aged 6-10 years) from local schools generated approximately 5,000 response records across four skill areas.

b) Historical Data: Approximately 15,000 response records from an existing educational platform.

c) Data Characteristics:

Feature	Statistics
Total Responses	20,000
Unique Students	150
Unique Skills	12
Average Responses per Student	133
Difficulty Range	1-5
Overall Accuracy Rate	68.3%

2) Feature Engineering

Feature	Type	Description
user_id	Categorical	Student identifier
question_id	Categorical	Question identifier
difficulty	Numerical	Pre-assigned difficulty level (1-5)
skill	Categorical	Knowledge component/skill
is_correct	Binary	Correct (1) or incorrect (0)
response_time	Numerical	Time taken to answer (seconds)
attempt_count	Numerical	Number of attempts on this skill
time_since_last_attempt	Numerical	Time elapsed since last attempt

3) Model Implementation

BKT Parameter Definitions:

Parameter	Symbol	Description
Initial Learning	$P(L_0)$	Probability student knows skill before any practice
Learning Rate	P(T)	Probability student will learn from an attempt
Guessing	P(G)	Probability of correct guess despite not knowing
Slip	P(S)	Probability of incorrect answer despite knowing

Parameter Values:

Parameter	Value	Rationale
$P(L_0)$	0.30	Moderate initial knowledge assumption
P(T)	0.40	Reasonable learning per attempt
P(G)	0.20	20% chance of guessing with 4 options
P(S)	0.10	10% chance of careless errors

The BKT model updates the student's knowledge state after each response using Bayes' theorem. The process can be visualized as follows:

Scenario: A Child Learning Addition

A 7-year-old child named Sarah is playing the "Learn with Me" game focusing on addition skills. She has attempted four addition questions so far, with the following history: correct, incorrect, correct, correct. The system now needs to determine her knowledge state before presenting the next question.

Initial Setup:

- $P(L_0) = 0.30$ (30% chance Sarah already knows addition)
- $P(T) = 0.40$ (40% chance she learns from each attempt)
- $P(G) = 0.20$ (20% chance of guessing correctly)
- $P(S) = 0.10$ (10% chance of slipping)

Step-by-Step Processing:

After Question 1 (Correct):

Prior knowledge before question 1: P(K) = 0.30

Predict correct answer:
P(Correct) = 0.30 × 0.90 + 0.70 × 0.20 = 0.27 + 0.14 = 0.41

Posterior after correct answer:
P(K|Correct) = 0.30 × 0.90 / 0.41 = 0.27 / 0.41 = 0.66

Apply learning transition:
P(K_new) = 0.66 + 0.34 × 0.40 = 0.66 + 0.136 = 0.80

Result: Knowledge increased from 30% to 80% after one correct answer.

After Question 2 (Incorrect):

Prior knowledge before question 2: P(K) = 0.80

Predict correct answer:
P(Correct) = 0.80 × 0.90 + 0.20 × 0.20 = 0.72 + 0.04 = 0.76

Posterior after incorrect answer:
P(K|Incorrect) = 0.80 × 0.10 / (1 - 0.76) = 0.08 / 0.24 = 0.33

Apply learning transition:
P(K_new) = 0.33 + 0.67 × 0.40 = 0.33 + 0.268 = 0.60

Result: Knowledge decreased from 80% to 60% after the incorrect answer. However, note that the knowledge didn't drop to zero because the model accounts for the possibility that the error was a "slip" rather than a lack of knowledge.

After Question 3 (Correct):

Prior knowledge before question 3: P(K) = 0.60

Predict correct answer:
P(Correct) = 0.60 × 0.90 + 0.40 × 0.20 = 0.54 + 0.08 = 0.62

Posterior after correct answer:
P(K|Correct) = 0.60 × 0.90 / 0.62 = 0.54 / 0.62 = 0.87

Apply learning transition:
P(K_new) = 0.87 + 0.13 × 0.40 = 0.87 + 0.052 = 0.92

Result: Knowledge increased from 60% to 92% after another correct answer.

After Question 4 (Correct):

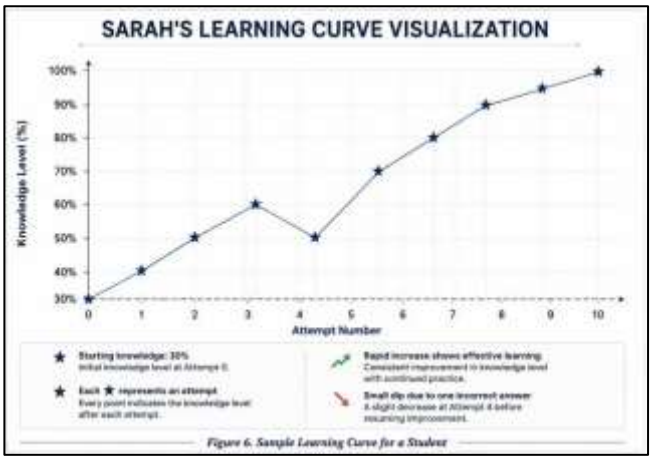
Prior knowledge before question 4: P(K) = 0.92

Predict correct answer:
P(Correct) = 0.92 × 0.90 + 0.08 × 0.20 = 0.828 + 0.016 = 0.844

Posterior after correct answer:
P(K|Correct) = 0.92 × 0.90 / 0.844 = 0.828 / 0.844 = 0.98

Apply learning transition:
P(K_new) = 0.98 + 0.02 × 0.40 = 0.98 + 0.008 = 0.988

Result: Knowledge increased to 98.8%, indicating near mastery of addition.



Mathematical Formulation of BKT =

$$P(K_t \mid Correct) = P(K_t) \times (1 - P(S)) / P(Correct_t)$$

Where:

P(K_t) is the probability the student knows the skill at time t.

P(S) is the slip probability.

P(G) is the guess probability.

If the response is correct:

$$P(K_t \mid Correct) = P(K_t) \times (1 - P(S)) / P(Correct_t)$$

If the response is incorrect:

$$P(K_t \mid Incorrect) = P(K_t) \times P(S) / (1 - P(Correct_t))$$

4. After Each Response:

The student's knowledge probability for the relevant skill is updated using the BKT update equations
The new knowledge probability is mapped to a recommended difficulty level using the mastery thresholds
The Game Engine requests a new question at the recommended difficulty level
The student receives personalized content that matches their current knowledge state

5. Mapping Knowledge to Difficulty:

For Sarah's addition skill at 92% mastery (Master level), the system recommends Level 5 (Very Hard) questions to continue challenging her. For her division skill at 28% mastery (Beginner level), the system recommends Level 1 (Very Easy) questions to build foundational understanding.

6. Continuous Monitoring:

The system continuously monitors each skill's knowledge probability. When a skill drops below a threshold, the system provides additional practice opportunities. When a skill reaches mastery, the system introduces new, related skills.

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