Ai Tutor System for Personalised learning and Adaptive Feedback using multi-agent system.

Michael Ayomide Ogunrinde

School of Computing and Digital Technologies, Sheffield Hallam University

Introduction and Background

Students learn in diverse ways and at varying paces, yet most digital tutors still rely on a one-size-fits-all model that cannot adapt in real time to student's strengths and weaknesses. AI Tutor addresses this by combining two powerful technologies: Deep Knowledge Tracing (DKT) and Large Language Models (LLMs). Unlike early approaches such as Bayesian Knowledge Tracing (Corbett&Anderson) which modeled skills in isolation, DKT uses recurrent neural networks to identify cross-skill patterns and predict student performance with greater accuracy. Meanwhile, LLMs now enable real-time generation of educational content, contextual feedback, and automated assessment. By integrating DKT's mastery predictions with LLM content creation. It provides an adaptive Year 6 mathematics environment that detects visual, sequential, and practice-oriented learning styles and provides a truly personalised tutoring system.

System Architecture

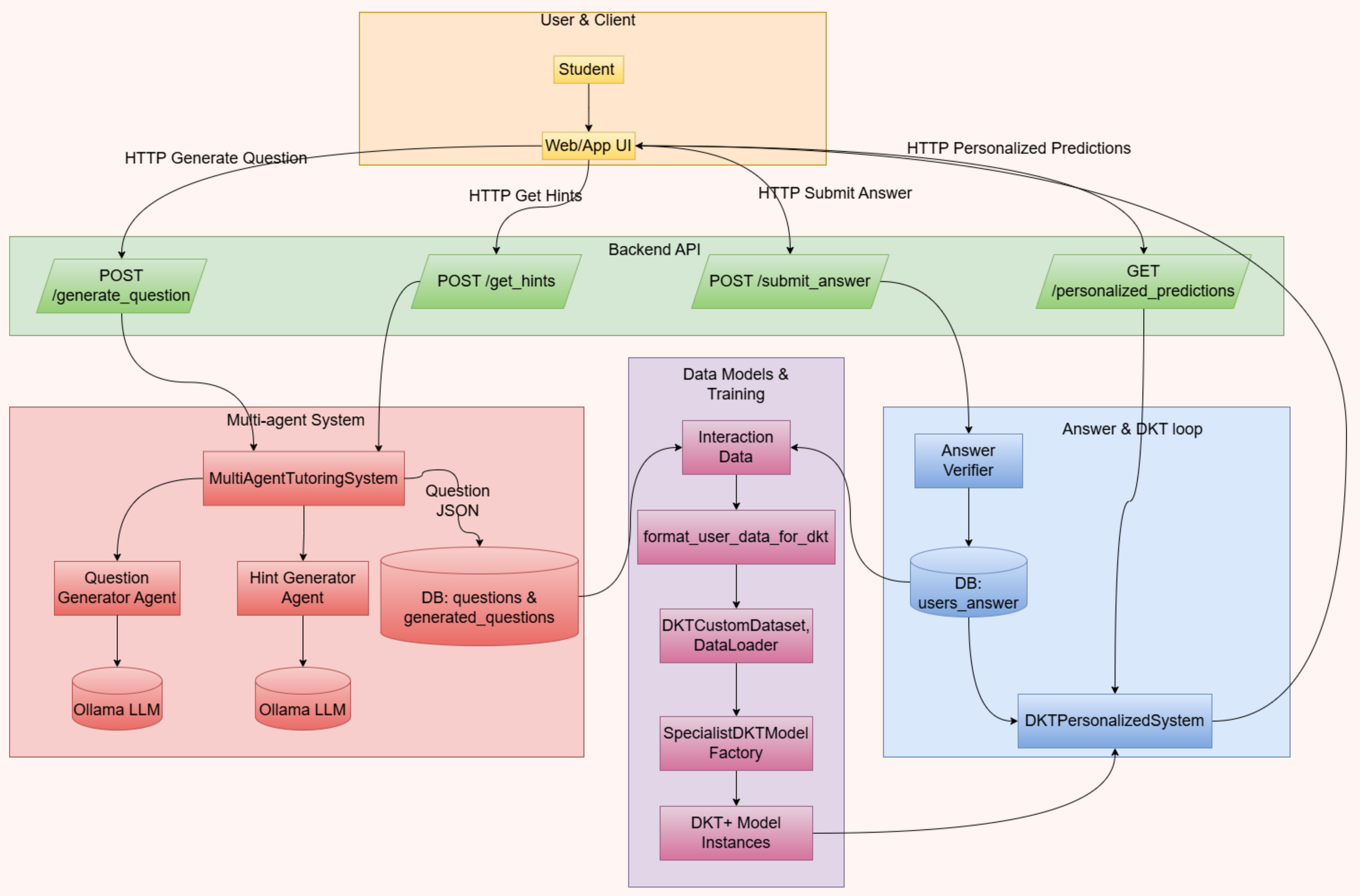

Figure 1. System Architecture

Key Components:

- **Multi-agent System**: Features Question Generator and Hint Generator agents powered by Ollama LLM
- **Backend API**: FastAPI implementation handling question generation, hint requests, and answer submissions
- **Data Models & Training**: Creates specialised DKT+ models based on learning style detection
- **Answer & DKT Loop**: Verifies answers and updates student knowledge state in real-time

Methodology

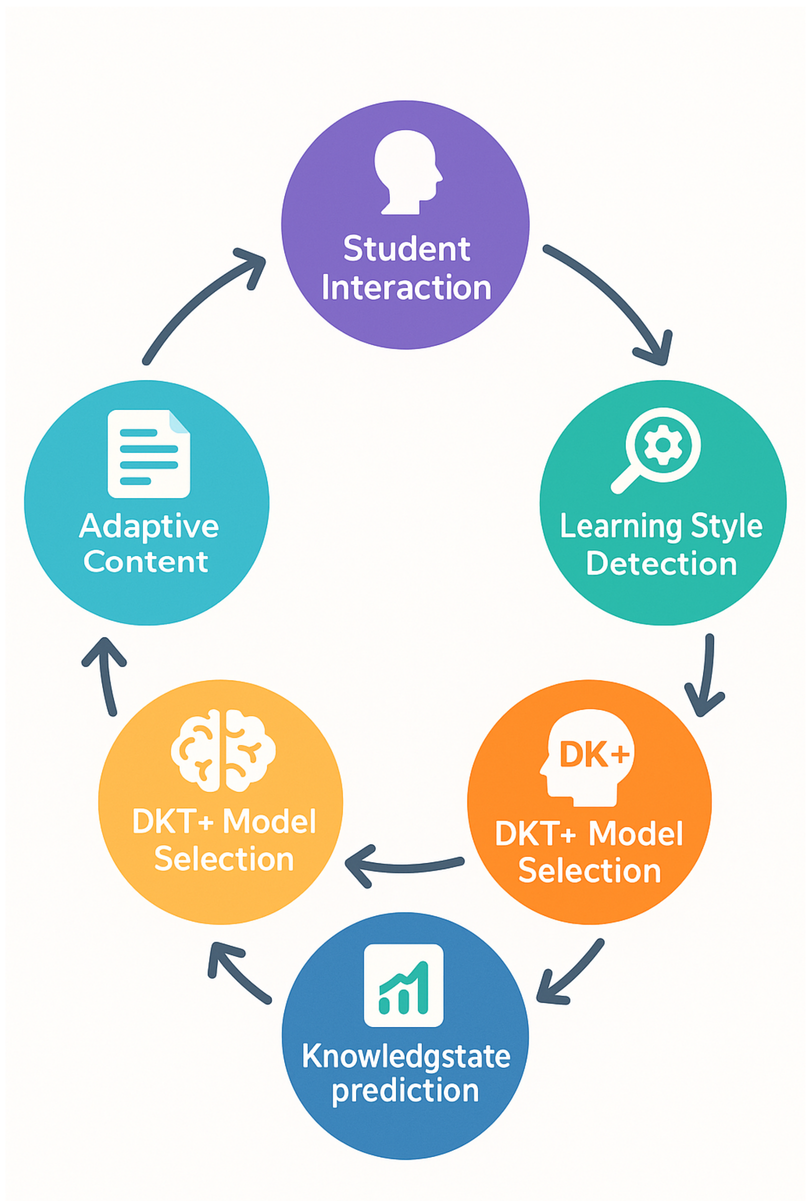

Figure 2. Methodology

Multi-Agent AI Tutoring Approach:

- **Data Generation** — Created synthetic training data with varied learning profiles to train specialist DKT+ models
- **Learning Style Detection** — Implemented heuristic analysis of student interactions to identify visual, sequential, and practice-oriented learning preferences
- **DKT+ Model Specialisation** — Developed separate prediction models for each learning style with optimised parameters
- **LLM Prompt Engineering** — Designed specialised prompts for Question Generator and Hint Generator agents to create age-appropriate content
- **Adaptive Content Selection** — Combined DKT+ predictions with learning style to select question type, difficulty, and scaffolding level

Results and Discussion

Learning Style Detection Performance

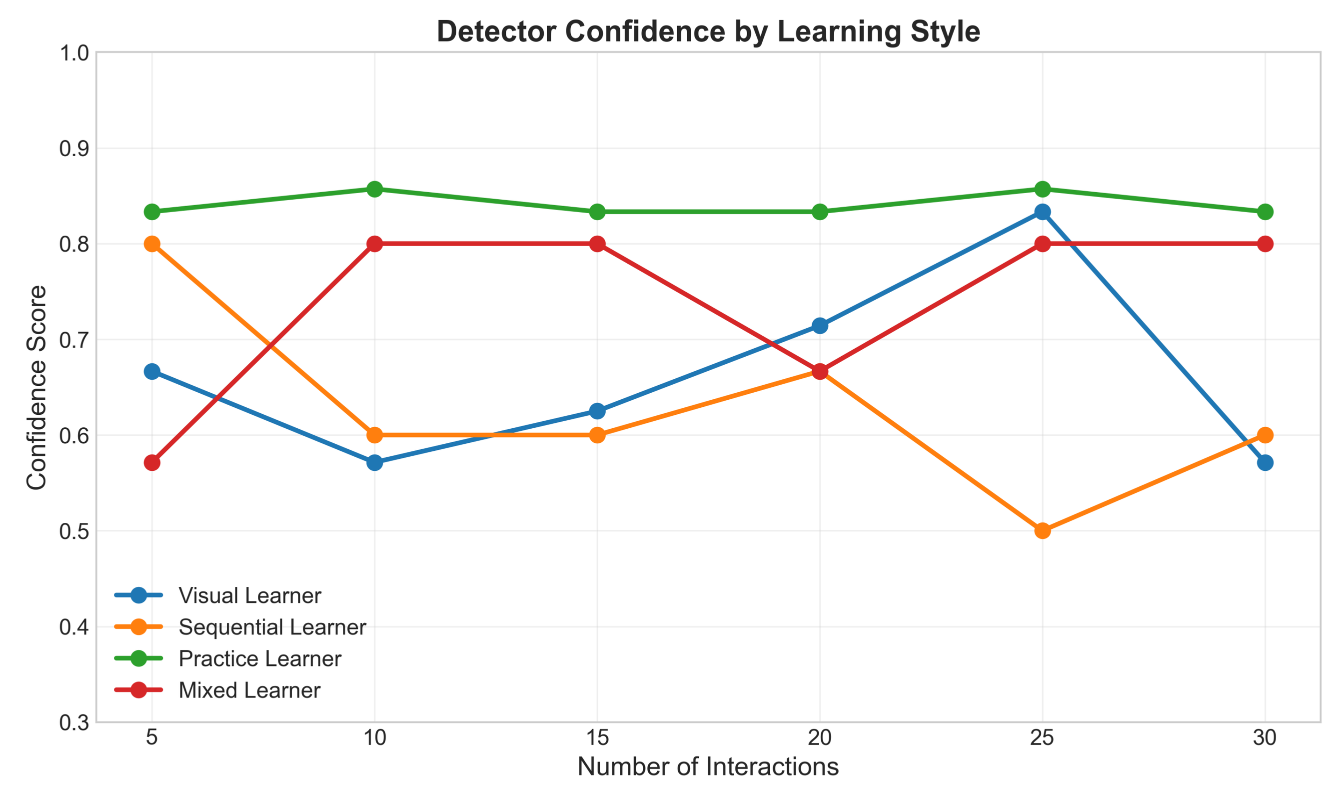

Figure 3. Detector confidence levels across learning styles with increasing student interactions

- **Detection Peaks**: Practice learners at 20 interactions (90 % confidence), visual learners at 10 (75 %), mixed learners at 25 (80 %).
- **Sequential Learners**: Exhibit a U-shaped confidence curve, dipping around 20–25 interactions before recovering.
- **Convergence & Onboarding**: By 30 interactions, all styles reach roughly 65–75 % confidence. Hence why 25-question needs to be answered because it yields enough data to hit high-confidence detection for practice (90 %), visual (75 %), and mixed learners (80 %), while clearing the low-confidence dip for sequential learners ensuring accurate personalisation from the first lesson.

DKT+ Model Performance

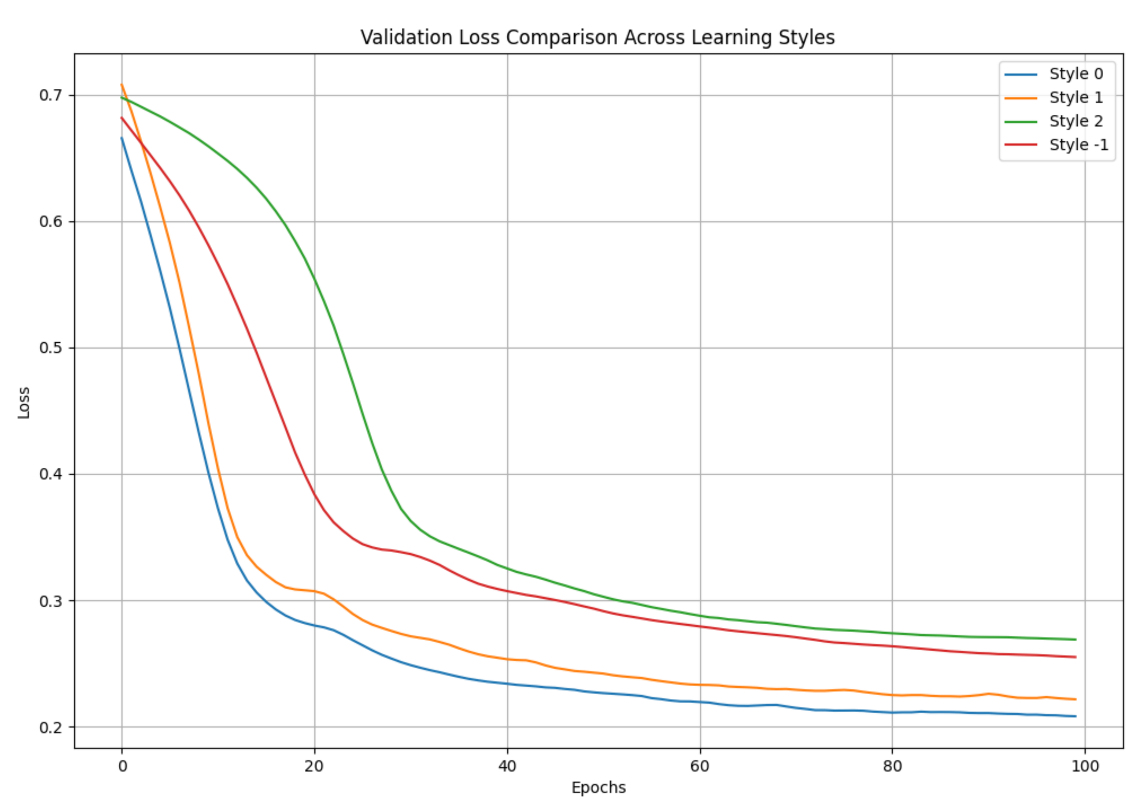

Figure 4. Validation loss comparison across specialist DKT+ models for different learning styles

- All specialist models demonstrated successful convergence, with training and validation losses decreasing consistently across epochs
- **Visual learner model (Style 0)** achieved the lowest final validation loss (0.20) and fastest convergence rate, showing strong specialisation benefits
- **Practice-oriented model (Style 2)** required more training epochs (40+) to converge but ultimately achieved stable performance
- **Default model (Style -1)** showed moderate performance, validating our hypothesis that specialised models outperform generic approaches
- None of the models exhibited overfitting, as validation losses continued to decrease or stabilise throughout training

Conclusions

- AI Tutor successfully combines adaptive knowledge tracing with personalised learning through a original multi-agent architecture that responds to both knowledge state and learning style.
- The specialised DKT+ models show clear training patterns with good convergence properties, demonstrating outstanding performance when matched to appropriate learning styles.
- The learning style detection system achieves high confidence identification within 20-30 student interactions, informing both content selection and hint generation.
- By requiring 25 initial questions during onboarding, the system gathers sufficient data to make reliable adaptations for most students.
- This work demonstrates the potential of combining generative AI content creation with data learner modeling to create a truly personalised educational experiences.

Future Work

- Implement gamification elements including points, badges, and leaderboards to improve the student engagement with the app.
- Develop dynamic learning style adaptation that continuously refines student profiles as interaction patterns evolve, ensuring personalisation remains accurate over time
- Improve content generation for visual learners through specialised LLM prompting techniques to create more effective diagrams, charts, and spatial representations

c2027880@hallam.shu.ac.uk