AI based Personalized Learning in Higher Education

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Introduction to Personalized Learning & AI's Role

What is Personalized Learning
Tailoring instruction, content, pace to individual student needs and preferences
Recognizing diversity in prior knowledge, cognitive styles, motivations, and learning contexts
Flexible pathways, adaptive assessments, and customized feedback for student-centered learning.
Enhances engagement and fosters deeper understanding.

How AI Helps in Personalized Learning
Automates and enhances data collection, analysis, and adaptation.
Monitoring learner behavior (performance, engagement, interaction) to build dynamic profiles.
Adjusts task difficulty, recommends resources, and provides individualized feedback.
Machine learning (e.g., BKT, DKT) predicts concept mastery and guides content sequencing.

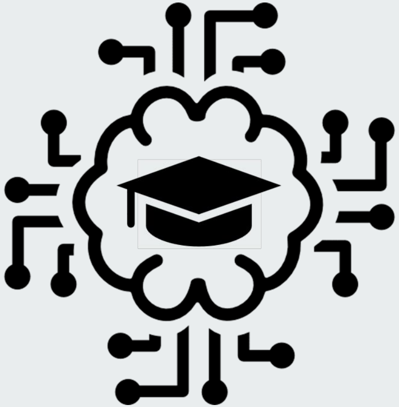
Why AI Personalized Learning Matters & Our Focus

- Automates real-time analysis and customization, bridging gaps in traditional classrooms.
- Leads to more equitable learning opportunities by identifying struggling students early.
- Uncovers hidden patterns in learning behavior to refine teaching strategies.
- Empowers educators to tailor their way of teaching to the individual students.

Research Question:

The goal of this report is to answer the question: "If the integration of AI based personalized learning systems for higher education is feasible with the current technologies"

The Evolution of AI in Education for personalized learning



Intelligent Tutoring Systems

Personalized learning through providing **pedagogically optimized** paths to learners, emulating the guidance of a human tutor. They adapt content delivery based on a learner's real-time performance.

Examples: Cognitive Tutor, ALEKS

Adaptive Content Recommendation

Personalized learning through **recommending** content based on the learner's prior interactions, preferences, and performance.

Example: Duolingo, MOOCs like Coursera or EdX

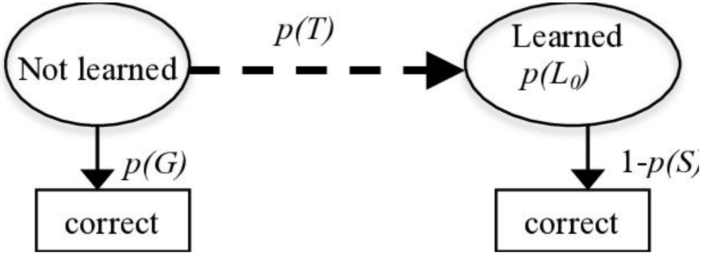
Knowledge Tracing

First Attempt: Bayesian Knowledge Tracing (BKT)

$$P(L_n|Correct) = \frac{P(L_{n-1})(1 - P(S))}{P(L_{n-1})(1 - P(S)) + (1 - P(L_{n-1}))P(G)} \quad (2)$$

$$P(L_n|Incorrect) = \frac{P(L_{n-1})P(S)}{P(L_{n-1})P(S) + (1 - P(L_{n-1}))(1 - P(G))} \quad (3)$$

$$P(L_n) = P(L_{n-1}|Action) + (1 - P(L_{n-1}|Action))P(T) \quad (4)$$

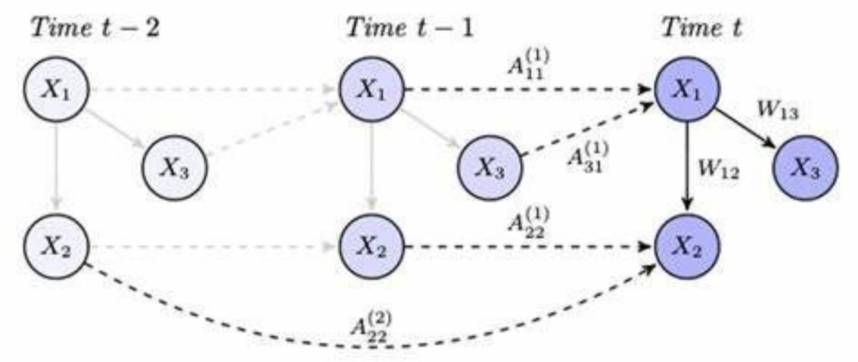


Estimates a learner's probability of mastering concepts through probabilistic inference.

Good results for structured knowledge like **math, spelling, and programming syntax**.

BKT **struggled in less-structured domains** like essay writing or problem-solving, where student behavior is harder to model using binary knowledge states

Dynamic Bayesian Networks for overcoming BKTs shortcomes



- Modeled **multiple latent variables** for richer understanding.
- Allowed more complex relationships between concepts.
- Incorporated elements like time and learner fatigue.
- Good approximation for the technology at the time

	BKT	DBN
Structure	One concept at a time per step	can track multiple skills and dependencies between them
Assumptions	Skills are independent; knowledge binary (known/not known)	Can model partial knowledge, cross-skill influence, and forgetting
Temporal Dynamics	Fixed over time	Can adapt over time, even include memory effects or external variables
Data use	Only uses correct/incorrect answers	correctness + time spent, hints used, or sequence of concepts

Advancements from 2015 to 2025

Deep Knowledge Tracing

- *DBN's on steroids*
- Learns complex, hidden patterns from student interaction sequences without requiring expert-defined models
- Lack of interpretability, instability under sparse data, and difficulty explaining recommendations to teachers or learners

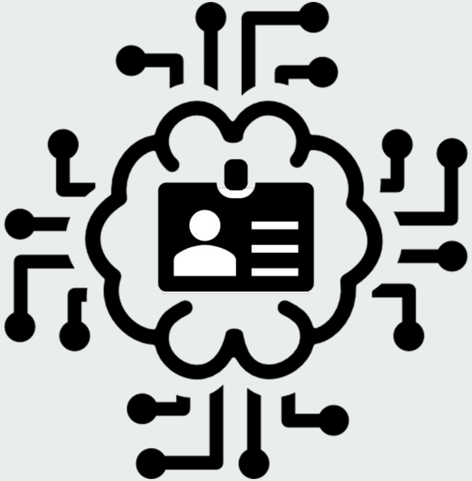
Reinforcement Learning and RLHF

- Optimizes the sequence of learning activities through an agent
- RLHF helps the agent redirect itself to accurate and relevant assertions
- Reliance on large interaction data and computational overhead limits its applicability

Leap towards LLMs (2023-Present)

- Chatbots for unstructured one on one interaction (personalized tutoring)
- Problems encountered
  - AI Hallucination due to uncontrolled Environments
  - Lacks long-term student knowledge profiling
  - Requires robust validation and human intervention

Student profiling



Why is it necessary? What do we have now? What is missing? How can we collect that data?

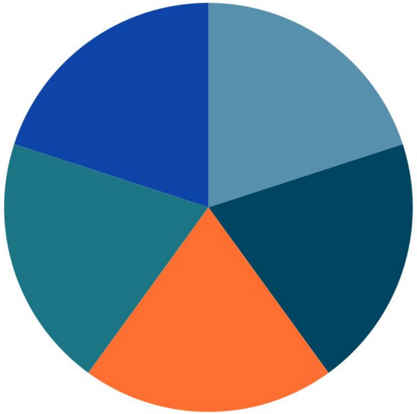
Why is Student Profiling Necessary in Personalized Learning?

- Students have different backgrounds, skills, and learning preferences
- One-size-fits-all education often fails to meet individual needs
- Profiling helps tailor content, pace, and method to the learner
- It increases engagement, retention, and overall performance
- Enables AI to deliver relevant, adaptive support

Personalized learning can only be effective if we understand who the learner is. A well-structured student profile provides the data needed to customize the educational journey, making learning more meaningful, efficient, and motivating.

Overview of Student Profile Components

- **Knowledge Factors**
- **Cognitive Factors**
- **Motivational Factors**
- **Behavioral Traits**
- **External Context**



A student profile includes key dimensions that influence how a person learns. These dimensions guide the personalization process in adaptive learning systems.

Knowledge Components

Base of Knowledge (Prior Knowledge)	Conceptual / Analogical Knowledge	Metacognitive Knowledge
Declarative knowledge: facts, concepts, definitions	Pre-existing mental models and conceptual frameworks	Awareness of what one knows and doesn't know
Procedural knowledge: processes, steps, problem-solving strategies	Analogies and similar concepts that can be used to explain new material	Ability to self-assess and reflect
Misconceptions: incorrect prior knowledge or misunderstandings	Example: Understanding electric current can help grasp the concept of blood circulation	Use of learning strategies (e.g., summarizing, planning, checking)

Cognitive and Learning Profile

Learning Styles and Preferences	Cognitive Style / Thinking Type	Memory and Cognitive Load
Visual / auditory / kinesthetic	Holistic vs. analytical	Working memory capacity
Reading / watching / interactive tasks	Sequential vs. global	Sensitivity to cognitive overload
Individual / collaborative / guided learning	Fast vs. slow but thorough	

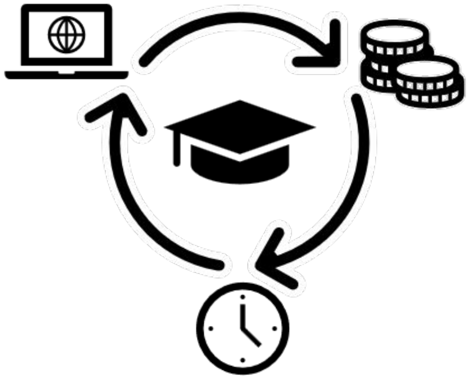
Motivation & Behavioral Factors

Motivational and Affective Factors
Type of Motivation • Intrinsic (internal interest) • Extrinsic (rewards, pressure)
Goal Orientation Performance-oriented vs. mastery-oriented
Emotional States Anxiety / curiosity / self-confidence
Persistence and Frustration Tolerance • How the learner responds to mistakes • How long they try independently before giving up

Behavioral Data / Digital Footprints
Learning Activity Metrics • Time spent on each task • Frequent error types
Interaction Patterns • When and how often they learn • When they ask for help

External Contextual Factors

External Contextual Factors
Age, linguistic background
Physical environment (noise, space, access to tech)
Cultural expectations
Time availability
Socio-economic background



What data do we already collect?

We already collect:

- Test scores and quiz results
- Attendance and participation data
- Clicks, time spent, and navigation behavior in learning platforms
- Assignment completion rates
- Simple self-assessments (sometimes)

Current student data collection focuses mainly on observable behaviors and performance metrics, such as grades, platform activity, and task completion. While useful, these insights provide only a surface-level understanding of the learner.

What is missing? (What data should we collect?)

We need more of:

- Learning preferences (visual, auditory, kinesthetic, etc.)
- Motivation and emotional state data
- Self-regulation habits (like how they plan, monitor, and reflect)
- Prior knowledge structure (how well-connected their concepts are)
- Real-world context or goals (why they want to learn something)

To enable truly personalized learning, we need deeper insights into students' cognitive, emotional, and motivational profiles—as well as their learning goals and context—not just what they do, but how and why they do it.

How can we collect that data? (What methods are available?)

- Surveys and self-assessment tools for learning styles and motivation
- Behavioral tracking (e.g. clickstreams, scrolling, pausing)
- AI-based knowledge tracing (e.g. BKT or DKT models tracking mastery over time)
- Natural language processing (NLP) to analyze student writing and discussion
- Emotion detection via webcam (facial expressions) or sentiment analysis from text
- Multimodal analytics, combining data from different sources (videos, quizzes, discussion, etc.)

A variety of data collection methods—ranging from self-reports to advanced AI and multimodal analytics—allow us to build richer student profiles. Combining these approaches helps capture not just performance, but the full learning experience.

Limitations of integrating AI-based Personalized Learning Systems into Higher Education

AI-driven personalized learning offers significant potential for tailored education, but its feasibility of widespread integration into higher education is challenged by various limitations.

Ethical concerns and Societal Implications

- **Data Privacy:** Extensive sensitive student data collection raises concerns about security, misuse, and trust; robust safeguards and regulatory compliance are vital.
- **Algorithmic Bias:** AI can amplify biases from training data, leading to unfair outcomes for marginalized groups and widening achievement gaps.
- **Equitable Access:** High implementation costs and unequal technology access exacerbate the digital divide, necessitating a focus on inclusive access.

Technical and Implementation Hurdles

- **Data Management & Accuracy:** Fragmented data and potential inaccuracies in AI output (due to training data limitations) hinder reliable and holistic learner support.
- **High Costs:** Substantial financial investment for implementation and maintenance is a significant barrier for many institutions.
- **Adoption:** Educator resistance, insufficient and training hinder successful integration.
- **Scalability:** Challenges in adapting AI across diverse contexts limits generalizability.

Best Practices and Real-World Success Stories

Best Practices for Implementation Personalized AI

Core Implementation Strategies:

- Establish Clear Educational Objectives - Technology serves pedagogical goals, not the reverse
- Implement Comprehensive Data Analytics - Track multiple learning dimensions while protecting privacy
- Ensure Continuous Feedback Mechanisms - Real-time progress monitoring and adaptive responses
- Foster Teacher-AI Collaboration - Human educators maintain oversight and contextual judgment

Critical Considerations:

- Privacy & Ethics - GDPR/CCPA(General Data Protection Regulation & California Consumer Privacy Act) compliance, data minimization, algorithmic bias monitoring
- Scalability - Robust infrastructure to support growing datasets and diverse environments
- Teacher Training - Comprehensive programs for AI interpretation and integration skills

Real-World Success Stories

The two main softwares these days in the AI Personal Learning

Squirrel AI Learning:

- Serves 24 million students across 3,000 learning centers worldwide
- Achieved 43.5% increase in knowledge mastery and 64.9% jump in answer accuracy during a 2-hour learning period. This remarkable improvement occurred during Squirrel AI's Guinness World Record challenge on September 21, 2024, where 120,000 students participated in synchronized online mathematics lessons.
- Nano-level knowledge decomposition: breaks subjects into 30,000 fine-grained components

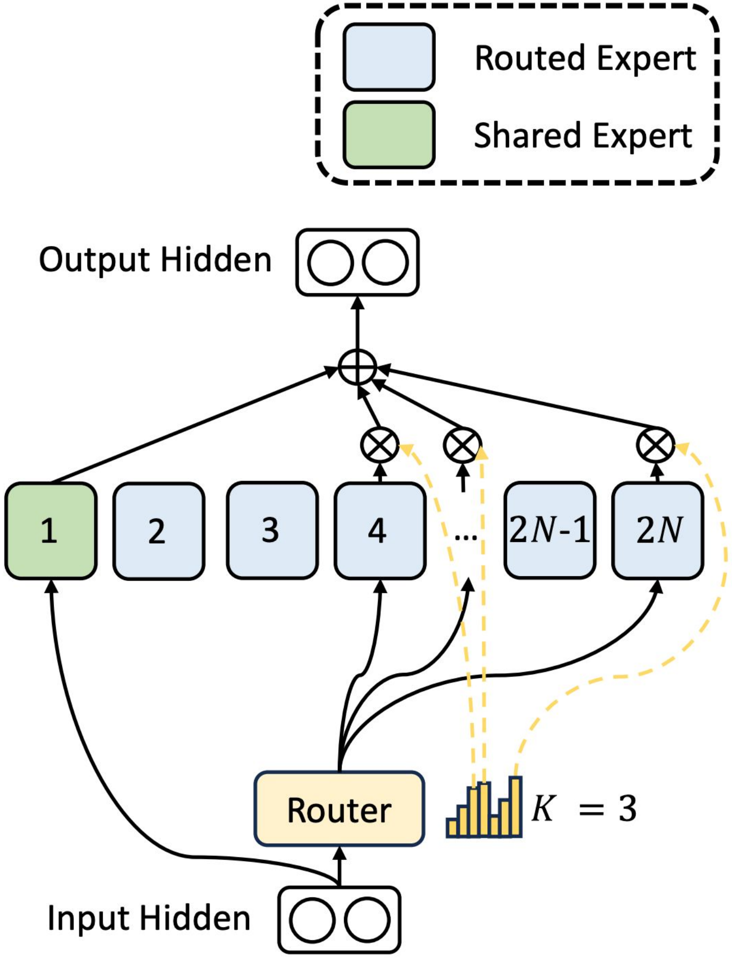
Khan Academy's Khanmigo:

- Uses Socratic(a form of cooperative dialogue that uses a series of probing questions to explore a topic, challenge assumptions) method to encourage critical thinking rather than direct answers
- Zero failing students in geometry classes after one semester implementation
- Integrates seamlessly with existing classroom workflows and traditional pedagogy

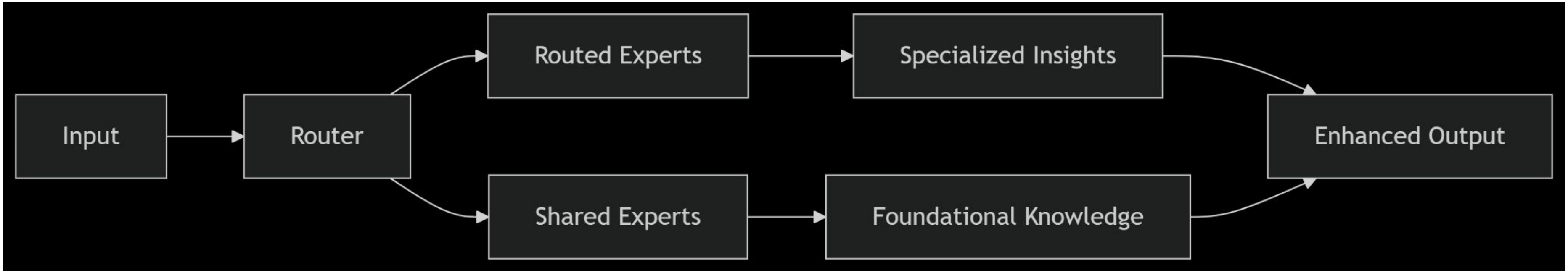
Key Takeaway: Both platforms demonstrate that AI can either revolutionize education (Squirrel AI) or enhance existing systems (Khanmigo), depending on implementation approach and institutional goals

Advanced MoE Architecture:

Fine-Grained Specialization and Shared Knowledge



Dataflow


Input
Router
Routed Experts
Shared Experts
Specialized Insights
Foundational Knowledge
Enhanced Output

Fine-Grained Expert Segmentation

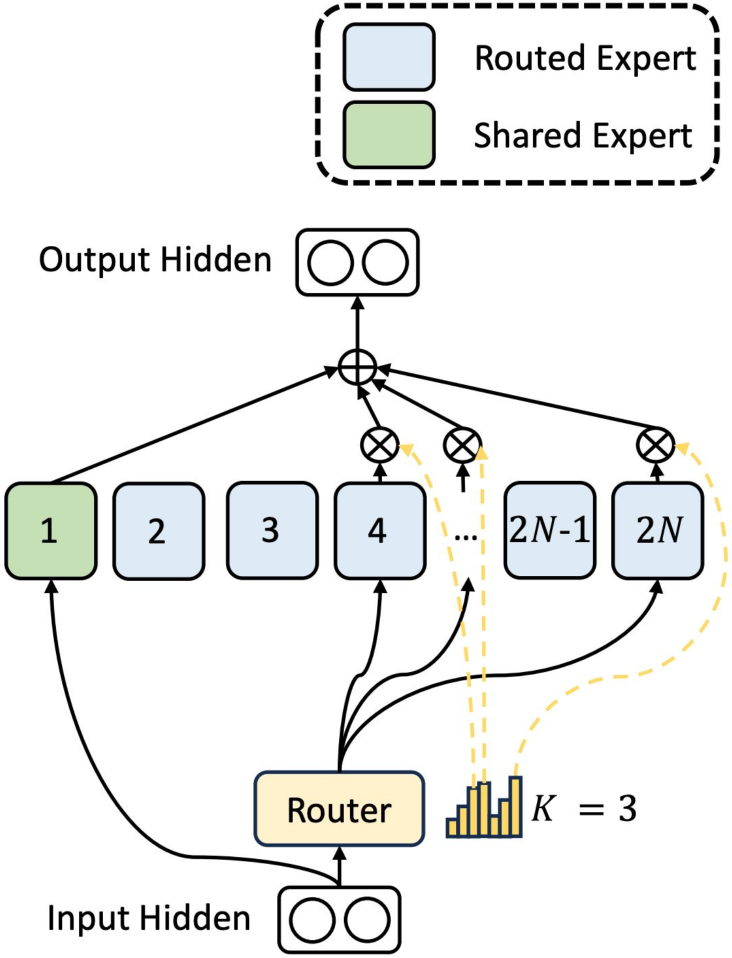
- Numerous small experts (100+ highly specialized units)
- Precise resource allocation (Router selects only top-K, e.g., K=3)
- Task-optimized performance

Shared Expert Integration

- Always-active foundation layer
- Provides cross-domain knowledge
- Complements specialized insights

Hybrid Advantage:

"Combines broad understanding with specialized responses for higher quality and efficiency"



Key Challenges of Advanced MoE Systems

Development & Operations

- More complex to set up and manage
- Troubleshooting takes longer
- Requires technical experts to operate

Performance Limitations

- Slower response times
- Extra coordination between experts needed
- Extra processing steps slow things down
- Not suitable for instant-response applications

Training Challenges

- Some experts get underused
- Difficult to balance expert roles
- Training process can be unstable

Resource Requirements

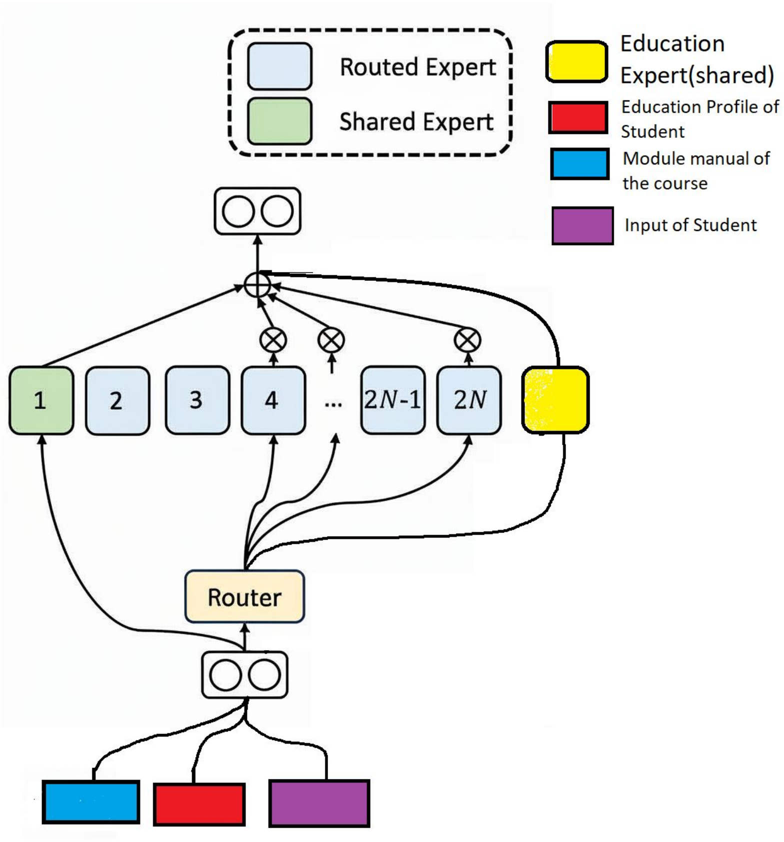
- Needs 3-5× more memory
- Requires stronger computers
- Uses more storage space

Deployment Constraints

- Not ideal for mobile devices
- Costs rise significantly at large scale

The Shared Education Framework

- Extending Evolutionary Path: Applies advanced architectural concepts to education.
- Core Principle: Utilizes a Mixture of Experts (MoE) architecture for personalized learning.
- Goal: Create a highly adaptive and tailored educational experience for each student.

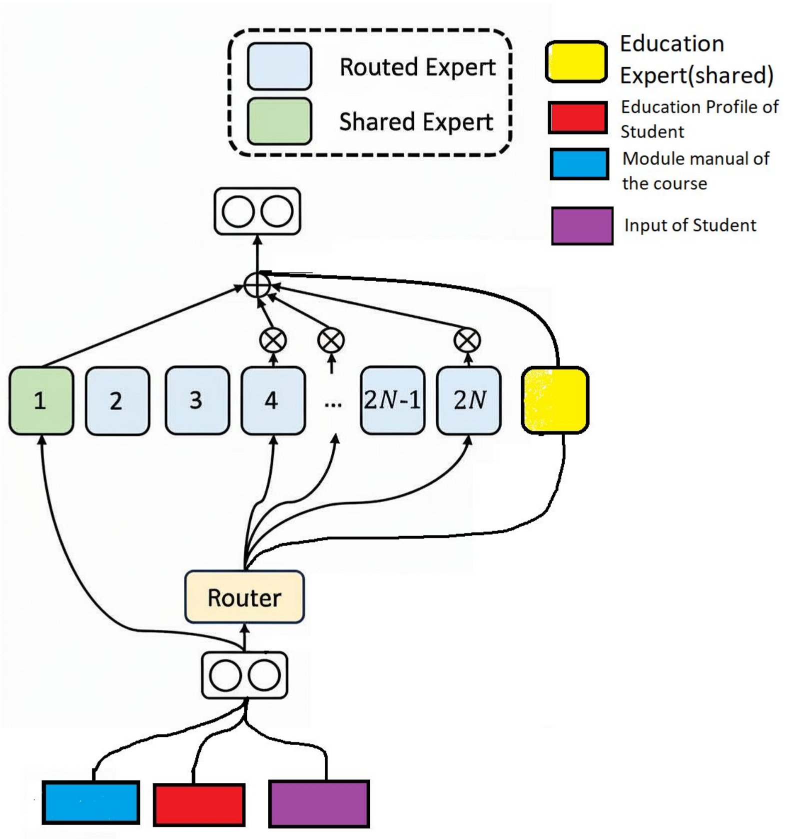


The Shared Education Framework

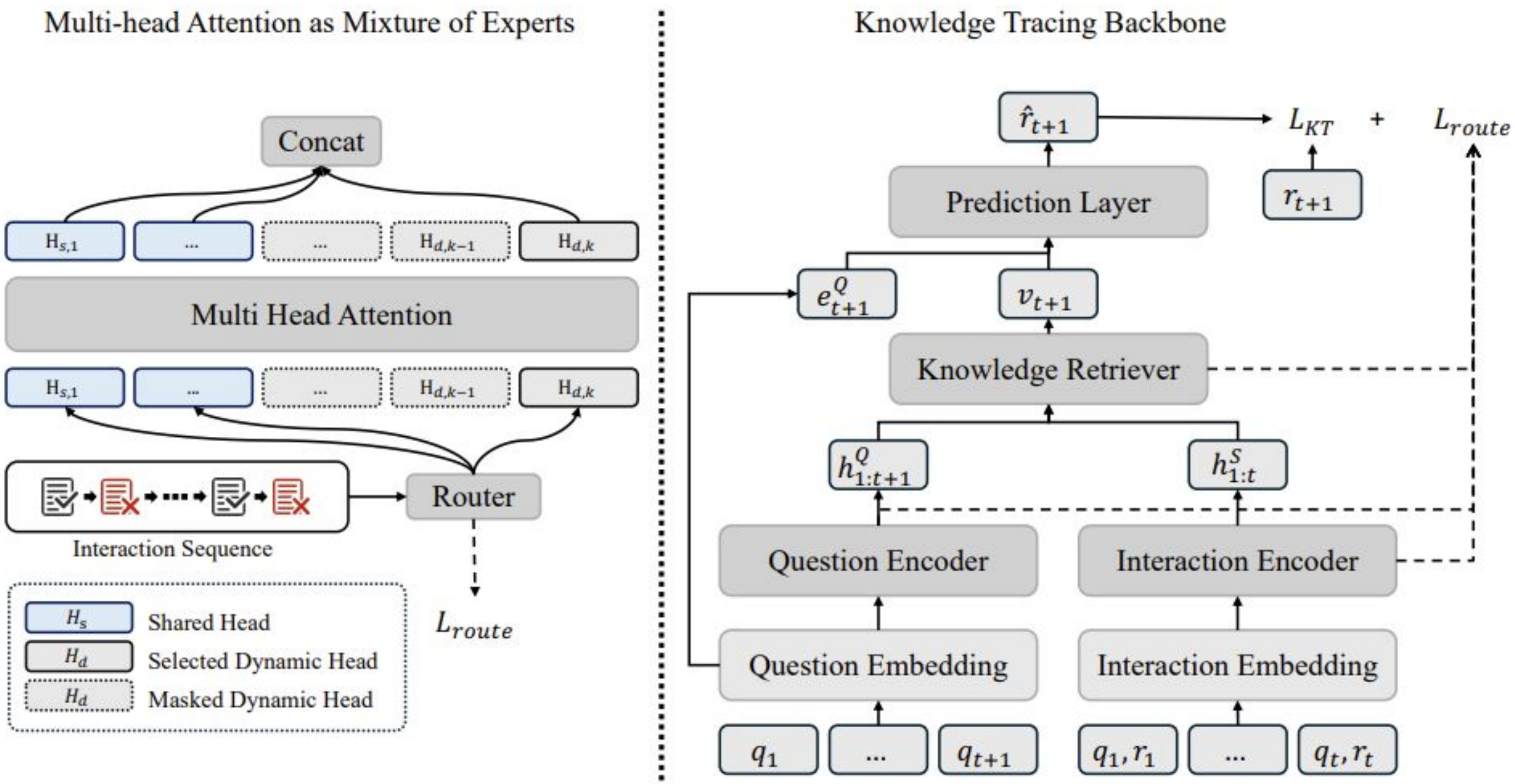
Dual Input for Tailored Selection: The router's decisions are informed by two key contextual sources:

- Education Profile of the Student: Captures individual learning patterns, strengths, and weaknesses etc.
- Module Manual of the Course: Provides information on course structure, objectives, and content.

Outcome: Precisely tailored expert selection based on individual needs and course requirements.



Non abstract representation from RouterKT



Conclusion

- While current technologies address some ethical and technical limitations, the feasibility of integrating AI-based personalized learning systems for higher education remains significantly constrained.
- Key limitations still include technical hurdles (data management, high costs, accuracy, faculty adoption, scalability) and ethical concerns (data privacy, algorithmic bias, equitable access).
- Ultimately, successful AI integration at scale requires strategic and ethical considerations that empowers educators and students.

Thank you for your attention.

Q&A