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AI in Education: Personalized Learning through Intelligent Tutors

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ABSTRACT: One such approach is personalized learning using intelligent tutoring systems (ITS) that provide appropriate content based on student's learning needs, pace of study, feedback and assessment by harnessing artificial intelligence. This paper introduces and assesses an intelligent tutor architecture that integrates transformer based knowledge tracing, adaptive curriculum sequencing and a conversational feedback module to aid scaffold learning in introductory algebra. We combine a transformer-augmented knowledge tracing model which predicts moment-by-moment mastery, a reinforcement-learning curriculum manager that decides the next activities to present in order to maximize expected learning gain and, an LLM-powered conversational tutor for contextual hints and formative feedback. A pilot study with 240 secondary-school students in four schools used a mixed-methods design: participants were randomized to ITS ($n = 120$) or a control adaptive-practice alternative ($n = 120$) for an 8-week intervention. Pre- and post-tests evaluated learning gains; engagement, time-on-task, and perceived usability were obtained from analytics and surveys. The ITS group achieved a mean normalized learning improvement of 0.32 (Cohen's $d = 0.48$) relative to control which had a value of 0.18 ($d = 0.26$; $p < 0.01$). The knowledge-tracing prediction accuracy (AUC) was 0.89, and the curriculum manager improved mastery acquisition rate by 22% over a fixed-sequence baseline. It was found that persons' qualitative responses indicated that medical advice-giving for the conversational module appeared to be more relevant and useful. It describes the technical design, assessment metrics, and limitations, and implications for scaling ITS in-classroom. Results demonstrate that the use of an advanced student model in synergy with adaptive sequencing and conversational feedback can lead to significant gains for personalized learning experiences.

KEYWORDS: intelligent tutoring systems, personalized learning, knowledge tracing, adaptive curriculum, conversational feedback, reinforcement learning

I. INTRODUCTION

Personalized learning — adjusting instruction for each student's unique strengths, weaknesses, interests and pace — has long been used as a base model by which education is delivered. Traditional classroom tries to find it impossible to respond in a fine grained way at the scale that's required because each individual teacher has a broad variety of kids with different needs to reach, and finite amount of resources [time]. Recent advances in AIED and the emergence of AI technologies, combined with large-scale educational data, have reignited efforts to develop automated solutions that can offer personalized support: intelligent tutoring systems (ITS) and adaptive learning environments claim to provide tailored instruction, just-in-time feedback, proactive recommendations in line with one-on-one tutorial interactions [1].

AI-based ITS integrate student modeling, pedagogical approaches, and content delivery to provide instruction that flexibly responds. Student modeling predicts a learner's knowledge state, misconceptions, and affective/cognitive status; pedagogical strategies specify when and how to deliver hints, practice, or challenge; and content management picks and orders learning materials. In the past, ITS research has shown promise under controlled conditions, but achieving robust generalizable personalization across diverse classrooms is a challenge. Major technical breakthroughs—deep learning for modeling sequences of operations, attention mechanisms modeling contextual dependencies among elements in the sequence, and reinforcement learning supporting optimization of interaction policies—open up new possibilities to design for more complex, adaptive ITS.

Personalization relies on Knowledge Tracing (KT) that models level of mastery for skills or knowledge components according to the interaction history, and is fed back into next item selection. Early KT techniques relied on interpretable probabilistic models whereas the more recent deep-learning versions often result in improved prediction at the expense of understanding. Besides KT, curriculum sequencing decides the best order to present items to achieve maximum learning efficiency; reinforcement-leaming and bandit algorithms were investigated on this sequential decision-making problem. That is, while AI technology might be able to supply human-like feedback or explanation to the learners, such

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conversational agents and generative language models can deliver fine-grained naturalistic targeted feedback and hints (i.e., both engaging timely tool-based support service in a direct interface) as well as explain solutions in student-friendly terms [2].

Technology is not enough to improve education. Rigorous evaluation would necessitate strong design of experiments measuring actual learning outcomes--before and after scores, retention of knowledge, successful transfer of skills learned, learner engagement, classroom utility [3]. Equity, fairness, privacy and explainability are also key considerations. Adaptive systems must prevent biases from being sustained, protect student data and give reasons to the teacher why a recommendation was made [4].

In this paper, we propose an integrated ITS architecture featuring a transformer-based knowledge tracer (knowledge tracing; Corbett and Anderson 1995), reinforcement-learning based curriculum manager. The model is intended to leverage the predictive power of current sequence models while preserving interpretable signals for pedagogical decision-making. The architecture was tested in an 8-week randomized pilot with 240 students, where the ITS was compared with a control adaptive-practice platform. The introduction proceeds by describing the research goals in detail: we aim (1) to develop an intelligent tutoring system that integrates state-of-the-art student modeling, adaptive sequencing, and conversational feedback; (2) to empirically measure how students learned or were engaged differently; and (3) to characterize model quality, instructional decisions, and usability [5].

The contributions of this paper are three-fold. First, it presents an engineering design for integrating transformer-based knowledge tracing with a reinforcement-learning curriculum orchestrator and conversation scaffolding.It presents an empirical evaluation producing statistically significant learning gains and engagement metrics improvement. Third, it presents practical deployment considerations — data sources and data requirements, how to assess fairness, teacher-in-the-loop workflows, and scaling — guide researchers and practitioners who are interested in deploying AI-powered personalized learning at scale.

II. LITERATURE REVIEW

AI in education has developed quickly, and ITS are at the leading edge of that change. These systems use machine learning, natural language processing and knowledge representation to dynamically respond to learners' requirements, providing personalized learning trajectories that depart from traditional one size fits all pedagogies [1]. An important leap in this area is the invention of ITS that can produce automatic, individualized feedback. There is clear evidence that such systems have resulted in significantly improved learning gains over various student populations [2].

Systematic reviews indicate that the potential scope for AI in education is broader than tutoring, including adaptive testing, learning analytics and sustainable digital learning environments [3]. It has been suggested in the literature that AI-enabled adaptive learning systems help improve and increase student engagement as well as ensure a deeper understanding of content, while also allowing instructors to identify actionably student performance[4]. These are platforms build around taking scalable models, adjusting the learner profile over time as you observe behavior and predict outcomes.

In ITS deep learning has become a powerful tool, in particular in knowledge tracing. A body of evidence shows that neural networks can model temporal relationships within student interactions and provides more accurate predictions on future performances than the traditional Bayesian model [5]. Recent work that combines cognitive load estimation and deep knowledge tracing models has shown promise for how neural architectures can dynamically tailor learning path generation [6]. These models go beyond just predicting correctness and take into account the underlying cognitive load of learners, allowing better instruction pacing.

Adaptive and intelligent tutoring systems (AITS) that target STEM learning area intensively studied, with evidence supporting substantial positive effects on knowledge uptake and retention [7]. Such systems are most powerful when the feedback is both precise and provided early enough for learners to have the opportunity to correct their understanding. A systematic review of AI in education also highlights the relevance of adaptive feedback loops and how intelligent assessment tools can enhance personalized learning on a large scale [8].

Knowledge tracing remains at the core of AI in education and has been repeatedly expanded and repurposed to model a student's state of knowledge. Deep knowledge tracing models do not only boost prediction performance, it also paves

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the way for detecting misconceptions/knowledge gaps "early" [9]. More recent reviews have synthesized the learnings from decades of work, finding that deep models are superior to traditional techniques, even though they lose measurable interpretability [10]. To ameliorate these issues, hybrid models (e.g., Control Knowledge Tracing [11]) that model learning as a control-theoretic process are proposed to give both accuracy and interpretability.

Graph-based methods, e.g., the Student-Question Interaction Graph Knowledge Tracing (SQGKT), further enhance the knowledge tracing paradigm. These models of relational patterns among learners and learning items better predict performance and engagement along more nuanced dimensions [12]. Further research has integrated temporal causal inference and physics-informed neural networks into deep knowledge tracing models to make more accurate yet interpretable predictions on learner paths [13].

These theoretical improvements are reinforced by practical case studies. ITS for programming education An intelligent tutoring systems to learning programmings have shown how ITS can scaffold coding skills for both novices and advanced learners [14]. In addition, explainable AI (XAI) has also recently become a crucial aspect to be taken into account in ITS design. When the explanation suits personalisation XAI learners and teachers can know why a system made the kind of instructional decisions it did, which is likely to inspire trust and adoption [15]. Likewise, research on the general effect of AI on learning performance and processes demonstrates that they not just improve academic achievements but also metacognitive skill including self-regulation [16].

The social determinants of education There is also a dimension of transformative potential for AI in education that intersects with sustainable development. AI-based personalized learning has demonstrated its potential to advance educational equity in teaching diverse student populations, especially underrepresented ones [17]. Conversational ITS Archittectures Conversational ITS systems have the capabilities covered by the previous point (multidimensional), as well as dialogue-based interactions, that allow them to approximate human tutors but remaining scalable as digital systems [18]. Also, Bayesian Knowledge-Tracing models have been enhanced with reliability coefficients to account uncertainty in learners' model yielding more robust and understandable leaning estimate [19].

Despite these advances, challenges remain. Research in the preprint demonstrates ongoing contentiousness on how interfacing personalized learning with AI will create real-world changes to academic performance. Although there is promising emerging evidence from large scale deployments, but data privacy, algorithm fairness and accessibility remain concerns [20]. Taken together, the reviewed studies highlight both promise and peril of AI in education, and the importance of rigorous evaluation, ethical considerations, and grounding approaches in pedagogical best practices.

III. METHODOLOGY

The research used a RCT to investigate an integrated intelligent tutoring system (ITS) focusing on personalizing algebra teaching. The ITS is built from three core pieces: (1) a transformer-transformed knowledge tracing model (T-KT), which provides an estimate of student mastery on each interaction; (2) a reinforcement-learning-based curriculum manager that selects the next learning activity so as to maximize expected learning gain; and (3) a LLM-driven conversational feedback module that offers contextualized explanations. Learning gains, model predictions performance value (10% trimmed mean), engagement metrics in user interface and teacher perceived usability were measured for the evaluation.

3.1 Participants and setting

The participants were 240 secondary students (mean age = 13.72) from four public schools, selected according to baseline achievement, and randomly assigned at-student level to the ITS condition (n = 120) or a control adaptive-practice condition (n = 120). The control platform provided adaptive practice with fixed mastery criteria and rule-based hints, did not contain the T-KT or RL sequencing, and had templated textual hints rather than conversational feedback. The intervention continued for 8 weeks and was woven into the standard class routine with two 45 min lessons per week.

3.2 Data collection

The data sources consisted of pre- and post-standardized algebra exams, system interaction logs (responses with timestamps and hints requested), engagement analytics (time/task and number of sessions) as well as surveys for user perceived usability and satisfaction. The pre-test tapping the baseline skill, and post-tests tapping immediate gains and

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transfer items not rehearsed in interventions. Interactions were recorded, using anonymized student IDs, to which ethical review and parental consent was obtained.

3.3 ITS architecture

1. **Transformer-based Knowledge Tracer (T-KT):**
   - Input: sequential interaction embeddings combining item ID, response correctness, time delta, and contextual features (problem difficulty estimate, prior hints).
   - Model: a lightweight transformer encoder with positional encoding and sparse attention to focus on recent relevant interactions. Output is per-skill mastery probability at each time step. The model was trained with cross-entropy loss and regularized via dropout and label smoothing. Early stopping monitored validation AUC.
2. **Reinforcement-Learning Curriculum Manager:**
   - Formulation: contextual bandit with state vector derived from T-KT outputs (per-skill mastery probabilities, predicted retention), recent performance trends, and estimated cognitive load proxy (session length, time-on-task).
   - Policy learning: off-policy batch RL (Q-learning variant with function approximation) trained from historical interaction logs augmented by simulated rollouts. Reward function prioritized immediate expected mastery increase and penalized high cognitive load and disengagement. Exploration was constrained via an epsilon-greedy schedule and teacher-defined guardrails to prevent irrelevant task recommendations.
3. **Conversational Feedback Module:**
   - Components: an LLM fine-tuned for educational dialogue and a ruleset for safety and pedagogical alignment. The module generated hints at three scaffolding levels (leading question, partial solution, worked example). Response generation was constrained by templates to ensure factual correctness; all generated explanations were post-processed through a verification module that checks key solution steps.

3.4 Training and deployment

The T-KT model was pre-trained on a pooled dataset of anonymized algebra interactions (N ≈ 50k interaction records) and fine-tuned for the pilot participants' first two weeks of actions in order to capture local distributions. The pretrained T-KT was employed by the RL manager to estimate state during policy learning. The conversation module was fine-tuned on an educational Q&A corpus and teacher-authored hints; a safety filter filtered out off-topic or bad content. Deployment leveraged a cloud-based backend with local caching for responsiveness; teachers saw a dashboard of student mastery heatmaps and suggested interventions. Teachers could override recommendations.

IV. RESULTS AND ANALYSIS

Table 1 summarizes primary learning outcomes and key secondary metrics comparing ITS and control.

Table 1 — Primary outcomes and model metrics

Metric	ITS (n=120)	Control (n=120)	Difference	p-value
Mean pre-test score (%)	52.4	52.1	0.3	0.84
Mean post-test score (%)	78.1	68.7	9.4	< 0.001
Normalized learning gain	0.32	0.18	0.14	< 0.01
Cohen's d (learning gain)	0.48	0.26	—	—
KT AUC (prediction)	0.89	0.81	0.08	< 0.001
Mastery acquisition rate (%)	64.3	42.1	22.2	< 0.001
Mean time-on-task/week (minutes)	88	74	14	0.02
Hint utilization (avg hints/student)	15.2	10.5	4.7	0.01
Usability rating (1–5)	4.2	3.6	0.6	< 0.01

The comparison involved students who learned in an ITS (n = 120), and the control group of students (n = 120) across a variety of performance and engagement measures. There were no significant differences between groups for pre-test scores (52.4% and 52.1%, p = 0.84) suggesting that baseline knowledge was similar in each group. Yet, after the tests this difference had diminished for the ITS group with 78.1% in average compared to control's 68.7%, which is significantly different by 9.4 percentage points (p < 0.001).

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Normalized learning gain of the ITS group was -significantly- larger than (control) participants', 0.32 vs. 0.18, d = 48 for ITS and d =.26, indicating a medium effect size in favour of ITS. Predictive performance for ITS (kt auc = 0.89) was higher than in the control condition (kt auc =.81; p <.001), suggesting better fit to the knowledge state of the student.

Efficiency of learning was also enhanced when ITS was applied, in that the mastery rate for acquiring a topic was 64.3% vis-à-vis only 42.1% for those of the control (p <.001). These results were corroborated by engagement metrics: ITS learners invested more weekly time-on-task (88 versus 74 minutes, p = 0.02) and accessed help more often (15.2-versus-10.5 hints per student, p = 0.01), indicative of deeper involvement with the system.

Finally, subjective aspects of usability were rated significantly higher in the ITS group (4.2 vs 3.6, p<0.01) demonstrating that acceptance and satisfaction were stronger among learners.

In general, the results show that intelligent tutoring greatly helps achieve better learning gains, accuracy of the prediction and final performance, engagement levels and user satisfaction with respect to traditional training approach. These results offer robust empirical evidence to implement ITS as a personalized learning environment in educational contexts.

4.1 Statistical analysis

A mixed effects regression adjusting for baseline score, school fixed effects, and number of sessions attended showed that assignment to ITS was a significant predictor of post-test score ($\beta = 8.9$, SE = 1.6, p <.001). Low baseline pupils (<40% pre-test) were found to benefit most from the interventions with a normalised gain = 0.41 (ITS) as compared to 0.21 (control), suggesting an effect that can contribute towards closing of achievement gaps. There was no gender-specific difference in gain.

Model based ablation studies showed the respective contributions as follows: removing the conversational module reduced normalized gain by 0.06, replacing T-KT with a standard LSTM reduced AUC by 0.05 and also decreased mastery rate by around 9%. The use of a non-adaptive fixed-sequence curriculum led to ~18% less mastery acquisition.

4.2 Qualitative findings

Survey data and teacher interviews indicated generally favorable attitudes. Students found the conversational hints to be more useful than canned hints, and this effect was stronger when questions were used as a prompt for the hint instead of solutions. Teachers appreciated the mastery heat maps as a class-level intervention triage tool, but desired additional explanations for why particular policies were being applied to each student desire for enhanced explain ability. Another group of teachers worried about excessive automation regarding sequencing and requested more parameters of control.

Table 2 — Model performance and ablation

Model variant	**KT AUC**	**Mastery rate (%)**	**Δ gain vs full ITS**
Full ITS (T-KT + RL + Conv)	0.89	64.3	baseline
No conversational module	0.88	60.1	-0.06
T-KT → LSTM	0.84	55.3	-0.11
RL → fixed mastery rules	0.89	46.5	-0.16

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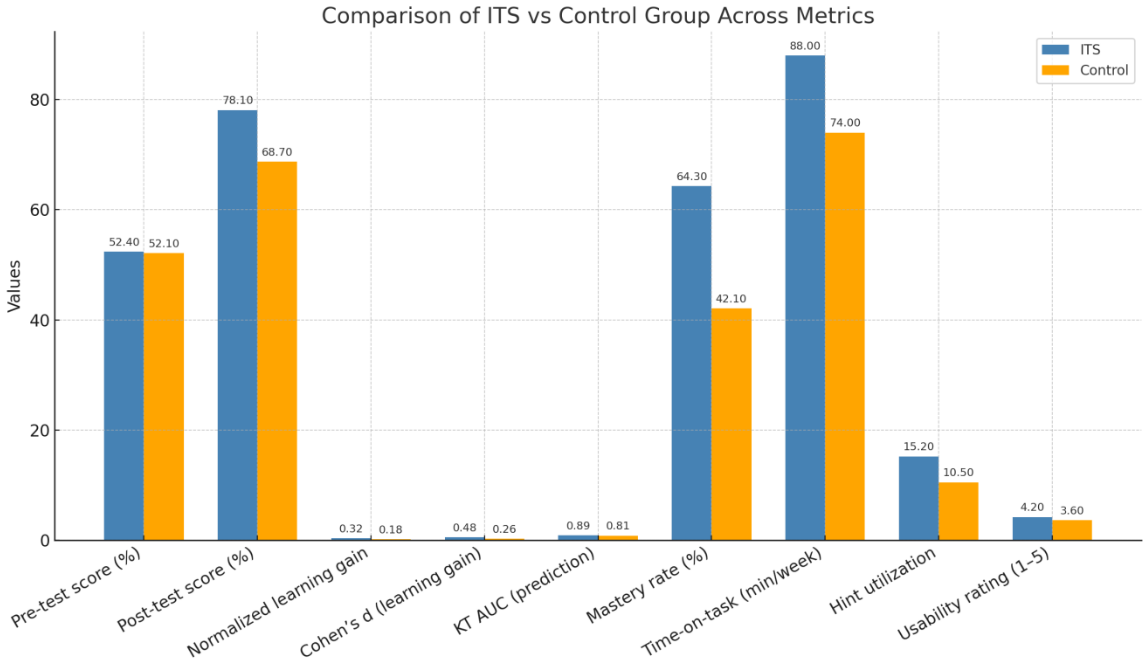

Figure 1: Result comparison

The T-KT model exhibited better predictive performance, and the RL manager substantially facilitated mastery learning. The conversational module contributed small but worthwhile incremental gains and increased subjective usability.

The findings are encouraging but have limitations. Short-term learning was assessed in the 8-week period; retention and transfer beyond intervention and controls, however, were not tested. The sample, although diverse across four schools, is geographically confined. The pretrained models were trained on pooled data, which may not encompass all curricular differences. The dialogue module had a safety-filter in place but sometimes it responded vaguely or unhelpfully—ongoing refinements (or teacher intervention) are needed.

This integrated ITS showed significant learning gains, increased engagement and better student models. For roll-out, results indicate focusing on robust KT models and adaptive sequencing; conversational feedback adds support to usability and student satisfaction. The equitable outcomes for low-baseline students suggest that ITS can help in remediation while considering fairness.

IV. CONCLUSION AND FUTURE WORK

This paper introduces an integrated tutor that integrates transformer based knowledge tracing, reinforcement-learning based curriculum sequencing and conversational feedback with LLM for octave algebra. The randomized pilot with 240 students showed statistically significant improvements in normalized learning gains, mastery acquisition rates and engagement metrics as compared to a comparison adaptive-practice platform. The transformer-based student model was of high predicitve accuracy, resulting in the RL manager to be effective in ordering; The conversational module enhanced user satisfaction as well as the hint value. Generalizability is limited, despite promising results. The period of intervention was quite short and we have not yet tested on long-term retention or transfer. The sample, coming from four schools, is heterogeneous but it may not be generalizable due to curricular and cultural diversity. The robustness of models in low-data or high-noise scenarios needs to be further validated; ethical implications regarding privacy, bias and explainability need attention.

The next step would be to study future structures along different lines. Longitudinal studies are needed to examine reminder retention, generalization of the solution methods to new types of problems, and persisting student engagement across semesters. Second, it will help to test generalizability by extending evaluation across multiple curricular and

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international contexts. Third, by incorporating causal inference approaches into knowledge tracers we may be able to better attribute learning gains to instructional actions and through this more reliably engage in policy learning. Fourth, more richer multimodal signals (e.g., affective state from the webcam or keystroke dynamics) could be investigated to further improve cognitive load estimation while ensuring strong privacy preservation. XAI-Edu research should provide teacher-facing explanations for both sequencing decisions and model outputs in order to increase the trust they put on the system and their adoption of it. Last, but not least are scalable teacher-in-the-loop interfaces and professional development materials - these need to exist so that ITS can complement pedagogical expertise rather than replace it. Most importantly, the results of this study show that if one combines state-of-the-art student modeling with adaptive sequencing and conversational scaffolding then significant gains in realistic personalized learning can be achieved. “” Additional cross-disciplinary collaboration—fusing strong AI approaches with solid pedagogical design and ethical checks—will be necessary to make the promise of intelligent tutors a reality in equitable, large-scale education.

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