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Enhancing Student Learning Through AI-Driven Content Personalization: A Study on Adaptive Learning Models in Higher Education

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Abstract

Artificial intelligence (AI) has been a transformational force in higher education today, providing new opportunities to differentiate instruction to meet individual learning needs. Despite the creation of multiple online platforms, digital assessments and automated feedback systems, many universities still use traditional, uniform teaching practices that do not cater for different learner backgrounds, motivations and cognitive preferences. Although AI-powered personalization is widely acknowledged as an exciting solution, empirical evidence on how well it works, especially in real classroom settings and in developing regions is scarce. This study addresses this gap by assessing the impact of an AI-based adaptive learning system that dynamically aligns the instructional content according to the performance trend, pace of learning and engagement behaviors of the students. The research will be conducted using a mixed-methods methodology, which will combine performance metrics and analytics, tailored content recommendations, engagement metrics, and surveys of student perceptions to analyze both the quantitative increase in learning outcomes and qualitative information about the perceptions of the learner. Findings show that AI-powered personalization has an important impact on improving academic performance, engagement, and be well received by students as supportive and accessible. The study adds to the practical and theoretical implications for the institutions who are interested in incorporating adaptive learning technologies, providing evidence-based recommendations for effective adoption in higher education settings.

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1 Introduction

Artificial intelligence has become an important component of modern educational systems, where universities are starting to use intelligent tools to support education and learning. The fast development of online courses, digital tests, and automated evaluation services have opened new possibilities to work with each student in accordance with their needs. In this growing digital environment, the concept of AI-controlled personalization has become an exciting potentially successful method of matching learning content to each student, their learning rate, level of performance, and learning needs. This development is of particular significance in higher education, where students frequently vary widely in their background knowledge, motivation and learning styles, and it is therefore difficult for instructors to implement a uniform teaching methodology.

Even with these new innovations, there are still numerous learning settings that make use of the traditional, one-size-fits-all model of instruction. Such methods may not be absolutely supporting for the learners who need more guidance or need different explanations. Current research also indicates that in addition to the growing spotlight placed on adaptive learning platforms, there is a gap in knowledge on how effective AI-based personalization truly is in actual classroom settings. In many contexts, particularly in developing regions, there is little empirical evidence of whether such systems are really improving learning outcomes, engagement and student satisfaction. Such ambiguity presents a practical and academic dilemma to the institutions that want to implement AI technologies in their curriculum.

This paper aims to fill this gap by focusing on the impact of AI-induced content personalization on student learning performance at the higher education level. The research investigates the quantitative gains in student learning results and qualitative information of student views on adaptive learning tools. The proposed approach involves the combination of performance tracking, personalized content recommendations, and student feedback to assess the effectiveness of the system.

The objectives of this research are as follows:

- To identify the key challenges and gaps in traditional learning practices within higher education.
- To develop an AI-based adaptive learning approach tailored to individual student needs.
- To assess the effectiveness of personalized learning using performance data, engagement indicators, and student feedback.
- To examine students' perceptions and acceptance of AI-driven personalized learning tools.
- To provide recommendations for integrating adaptive learning systems into higher-education environments.

This paper is divided into several sections. The literature review is a presentation of relevant studies on AI in education and adaptive learning. The methodology is used to describe the research design and the data collection process. The proposed framework describes the personalization mechanism that was utilized in this study. The results and discussion sections interpret the results and the paper ends with recommendations for future research.

2 Literature Review

Recent research on artificial intelligence in higher education indicates that AI can be used to support personalized and adaptive learning. Systematic reviews indicate that properly designed AI systems have the potential to enhance cognitive and satisfaction among learners over non-adaptive interventions, although many of them report small sample sizes and brief treatments to the detriment of limited studies and interventions[1].

Studies which focus on pedagogy stress on how personalization is as much a pedagogical challenge as it is a technical one. Personalization needs to be consistent with learning theories such as constructivism and needs to take into account student profiles, learning paths and assessment strategies. Educators should be able to analyze the analytics and modify teaching based on the analysis of the analytics results [2]. Other analyses detail how AI personalizes materials and feedback; they mention that AI does not displace teachers but reassigns them to the role of mentor, interpreting and coordinating data, and pointing at the issue of teacher preparation, digital inequality and school infrastructures[3].

Recent advances show the usage of AI techniques in supporting personalization. Sharif and Uckelmann present a multimodal framework where they apply reinforcement learning and multimodal streams of data to give privacy conscious feedback and show that it can be effective in enhancing adaptive learning [4]. Murtaza et al. survey the field of AI based e learning systems, their requirements, challenges as well as their modular architectures, identifying open research questions addressing content tailoring [5]. Essa, Celik and Human-Hendricks review the machine learning methods for identifying learning styles and observe an increasing interest in neural networks and a need for more empirical comparison studies [6]. Pardamean and colleagues come up with a collaborative filtering model based on which students are recommended relevant materials depending on their styles and report better learning results [7].

At the model level, deep learning is being used to predict learner performance and recommend personalized content sequences. Naseer et al. integrate deep learning with learning analytics to recommend content and observe improvements in achievement and satisfaction; they caution about data quality, model interpretability and the risk of reinforcing performance gaps [8]. At this larger level, Strielkowski and colleagues associate adaptive learning technologies with sustainability ambitions citing that AI has the potential to enhance efficiency and widen access with the concern of algorithmic transparency, privacy, and extended institutional capacity[9].

The adaptive learning analytics research also demonstrates the possibilities of AI to enhance the performance of students. Khosravi and co.-authors create an adaptive learning analytics framework coupled with an intelligent tutoring system and evaluate it across a variety of courses. They discover that AI generated feedback enhances mastery, particularly in the case of learners that tend to perform below average, and emphasize the importance of providing explainable advice to establish trust in students [10].

All these studies emphasize the idea that AI-based personalization may enhance student interaction, modify teaching in real-time, and assist data-driven learning processes, but they also emphasize that clear algorithms, well-thought-out pedagogy, and continuous assessment are necessary to make the implementation of personalization in higher educational institutions effective and fair.

Evidence from diverse contexts is emerging to suggest that achievement gaps can be reduced and varied learners served by adaptive learning. Wong et al. consider the adaptive system in the first-year classes and discover that the individualized pace and hints result in higher grades, especially in students with less previous knowledge [11]. A large scale systematic review by Zawacki-Richter and colleagues finds adaptive learning and predictive analytics to be the two most impactful forms of AI application and finds that to realise these benefits institutions need to invest in digital readiness and teacher training [12].

The recommendation literature shows that AI based systems can provide more accurate feedback when they combine techniques such as clustering and deep learning. Romero and Ventura review educational data mining algorithms and conclude that hybrid models outperform simpler rule-based approaches [13]. Harley et al. develop a taxonomy for emotion-aware learning technologies, showing that detecting and responding to learners' emotional states can enhance engagement and learning effectiveness, providing a foundation for integrating affective analytics into tutoring systems [14].

Research on intelligent tutoring systems continues to be central to personalization. Nye traces the evolution of these systems and shows that recent platforms incorporate deep learning and reinforcement learning to approximate human tutors in complex skill acquisition [15]. Widono et al. propose a framework for designing personalized learning systems in outcome-based education, using data-driven modelling, machine learning, and natural language processing to generate individualized learning trajectories and support continuous learner monitoring [16]. Sibley et al. investigate how students' academic self-concept and prior knowledge influence the effectiveness of generating technology-mediated explanations; they find that students with stronger self-concepts and more prior knowledge benefit more, suggesting that personalization should account for individual cognitive and motivational factors [10].

Ethical considerations remain paramount. Doroudi and Brunskill examine fairness and equity in adaptive learning, warning that personalization can unintentionally reinforce inequalities if algorithms are poorly designed [17]. They urge researchers to evaluate personalization through ethical and fairness lenses, especially in high stakes educational settings. Overall, the increasing number of published works demonstrate that AI based personalization, no matter how well implemented, can only be successful if it is based on appropriate pedagogy, transparent and fair algorithms, teacher readiness, and institutional capacity. A brief comparison between the most relevant recent studies in terms of methodology, datasets and identified weaknesses is given in Table 1.

Table 1: Compact Summary of Key Recent Studies on Personalized AI-Based Learning

Study	Methodology	Dataset	Weaknesses
Sharif and Uckelmann (2024) [4]	Reinforcement learning with multimodal learning analytics	Small university-level multimodal dataset	Limited generalizability; privacy constraints restrict data richness; RL model sensitive to reward tuning.
Murtaza et al. (2022) [5]	Systematic survey and architectural analysis of AI-based personalized e-learning systems	No empirical dataset (survey-based)	Lacks experimental validation; recommendations not tested on real learners; broad scope leads to uneven depth.
Essa et al. (2023) [6]	Systematic review of ML techniques for learning-style prediction	Reviewed datasets from prior ML studies	Insufficient comparative empirical studies; limited evidence on deep learning effectiveness; inconsistencies across reviewed datasets.
Naseer et al. (2024) [8]	Deep learning integrated with learning analytics for content sequencing	LMS log data from higher-education courses	Model interpretability issues; heavy dependence on data quality; risk of reinforcing existing learning gaps.
Widono et al. (2024) [16]	Predictive modelling, NLP, and analytics for personalized OBE pathways	Institutional academic records and learner submissions	Framework not tested at scale; NLP components limited to simple use cases; lacks long-term performance evaluation.

3 Methodology

This research uses a mixed-methods research design to assess how AI-driven content personalization can be used in higher education. The methodology combines the quantitative learning performance measures with the qualitative perceptions of students, which can provide an overall knowledge of the impact of adaptive learning models on the educational experience. The approach is organized in five major parts: research design, participants, AI personalization system, data collection procedures, and data analysis techniques.

3.1 Research Design

A quasi-experimental design was adopted to compare two groups of students, namely, a control group involved in traditional instruction and an experimental group using an AI-driven personalized learning system. The design allows differences in learning outcomes to be assessed, controlling for confounding variables such as course content, instructor and assessment format. The implementation of the study was conducted for an entire academic term in order to have sufficient exposure to the personalised learning environment and to obtain meaningful behavioural and performance data.

The mixed-methods approach was chosen because of its potential to merge performance metrics with student perspective. Quantitative data collection measures gains in academic performance and activity and qualitative data obtain information about the experiences of students in the practice of personalization. This intersection is critical to the comprehension of not only the effectiveness of AI-led personalization, but also its form and reason as an influence on student learning.

Participants were undergraduate students who were enrolled in a core course at a higher education institution. A total of 120 students participated in the study that includes 60 students in the experimental group and 60 students in the control group. The assignment was based on existing class sections so as not to disrupt the course schedule. Respondents had various levels of experience using digital learning tools, academic background and learning abilities. To assure ethical compliance, students were informed of study goals, procedures of data collection and confidentiality measures. Participation was voluntary and students could choose not to take part in the study at any stage and were not penalised academically.

3.2 AI Personalization System

The artificial intelligence personalization system created in the context of the current research combines three major elements that collaborate to create personalized learning trajectories, learning modeller, adaptive content recommender, and performance tracker. The system is continuously gathering student interaction data such as responses to quizzes, amount of time spent on activities, navigation pattern, etc. Based on these inputs, it processes these to estimate the evolving knowledge state of each learner. The learner profile is updated in real time with a machine learning model that can detect the areas of strengths, challenge and possible misconceptions.

Based on the current model of learners, the adaptive content mechanism searches for appropriate learning materials from a structured content bank. These resources contain videos, explanation of reading, practice tasks which differ in complexity. The recommendation logic takes variables such as semantic similarity between content items, estimated cognitive load, and the learner's performance in the past to determine the best order of instructional items. The system is dynamic in having the learning path adjusted as the students advance, which means that every next activity corresponds to the readiness level of the learner and can facilitate the gradual acquisition of knowledge.

In parallel, the performance monitoring component gives automated feedback to both students and instructors. Students are provided with visual cues of where they are in their mastery and next steps for them to take, as well as reminders to return to difficult areas. Instructors are given aggregated analytics, including trends in mastery of topics and summaries of engagement, that can help them identify learners that need to be targeted with support. Together these components constitute a closed-loop adaptive learning cycle, through which learner behaviour is continuously evaluated and recommendations updated to increase levels of personalization.

To illustrate the structure of the system, Table 2 summarizes the main functions performed by each component of the AI-driven personalization framework.

Table 2: Components of the AI Personalization System

Component	**Description**
Learner Modelling	Tracks student knowledge state, learning speed, and performance trends using machine learning models.
Content Recommendation	Selects and sequences learning materials based on difficulty estimation, semantic similarity, and learner readiness.
Performance Monitoring	Provides automated feedback, mastery indicators, and analytics dashboards for both learners and instructors.

3.3 Data Collection

Data collection for this study focussed on three main dimensions: academic, behavioural engagement and student perceptions. Academic performance data was collected using a pre-test given at the start of the course and a post-test at the end of the course. The tests assessed conceptual knowledge, problem-solving skill, and use of course materials. The scores obtained were used as a basis to measure learning gains between the control and experimental groups.

The learning platform generated activity logs which provided the data on behavioural engagement. These records included data like how much time students dedicated to learning resources, how many activities students finished, how frequently they had to review learning material, and how they went through suggested learning paths. These indicators generated by the system offered objective data of the way the students engaged in the individualized learning setting.

Student perceptions were gathered by using structured questionnaire distributed at the end of the study. The survey included items on perceived usefulness, ease of use, satisfaction and clarity of the personalised recommendations. A minor fraction of the survey was supplemented by the short interviews with the students to provide more qualitative information about their experience with the AI-driven system.

To illustrate the collected data, Table 3 presents a sample of anonymized data points used in the analysis. These values demonstrate the structure of the dataset and the types of indicators extracted during the study.

Table 3: Sample of Collected Data Points

Student ID	**Pre-Test**	**Post-Test**	**Engagement Score**	**Satisfaction (1–5)**
S12	56	78	0.64	4
S27	49	72	0.58	5
S41	62	84	0.71	4
S53	51	69	0.47	3

In addition, Figure 1 provides a visualization of engagement levels across a subset of students. This plot demonstrates how the data collected through system logs were used to observe behavioural differences between learners with higher and lower performance improvements.

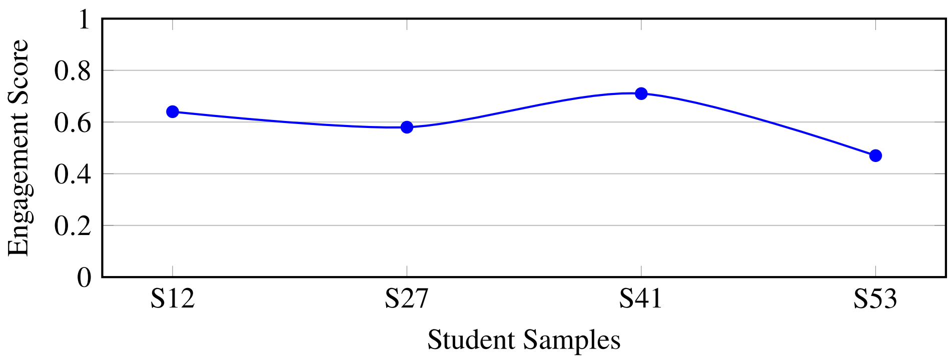

Figure 1: Engagement scores collected from system logs for sample students.

In general, the quantitative measurements of performance, the behavioural metrics provided by the system, and the qualitative data of perception formed a complete picture of assessing the efficiency of AI-based personalized learning.

3.4 Data Analysis

To compare the difference in learning gain and engagement between the two groups, quantitative data analysis was done using descriptive statistics, paired-sample t-tests, independent-sample t-tests, and analysis of variance (ANOVA). Effect sizes were calculated to determine the magnitude of differences that were observed. Engagement metrics were analyzed with the help of the correlation analysis to find the relationship between system usage and performance outcomes.

Qualitative data from interviews were analyzed by using thematic analysis. The coded transcripts were coded, and the common themes and patterns that occur were identified. The triangulation of quantitative and qualitative findings enhanced the validity of the conclusions by giving multiple perspectives on the effectiveness of the AI-driven personalization system.

Overall, the methodology has both an excellent combination of the rigor of experimental controls and the quality of qualitative information, and it provides a comprehensive assessment of the application of AI-based personalized learning in higher education.

4 Proposed Framework

The suggested framework combines three AI models which are integrated to work jointly to produce adaptive and personalized learning pathways. These models describe the changing knowledge state of the learner, the representations of instructional materials in a hierarchical semantic space, and the optimal sequence of tasks calculated by using the reinforcement learning. The model has been created as a closed-loop mechanism: once all the interactions between the student and the models are complete, all three models update their inner state, and the next learning recommendation can be formulated in a way that aids the student progression in a specific manner. The three models form the computational backbone of the system, and each contributes a distinct yet complementary function. The overall workflow of the proposed adaptive learning framework is illustrated in Figure 2.

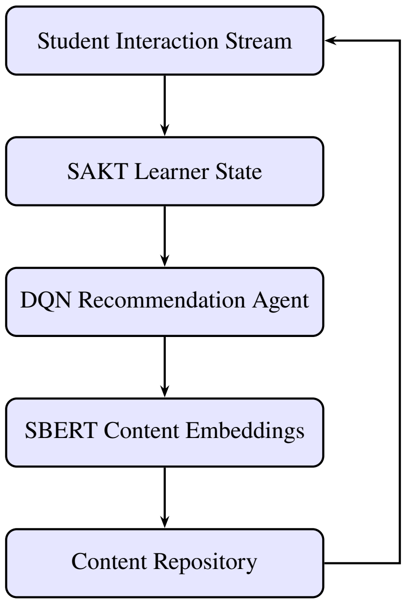

Figure 2: Compact workflow of the proposed adaptive learning framework integrating SAKT, SBERT, and DQN.

4.1 SAKT Model

The Self-Attentive Knowledge Tracing (SAKT) model estimates the learner's latent knowledge state based on historical interactions. Let the observed sequence of question–response pairs up to time t be expressed as

$$X_t = \{(q_1, a_1), (q_2, a_2), \ldots, (q_t, a_t)\}. \tag{1}$$

Each question q_i is mapped to an embedding $e_i \in \mathbb{R}^d$. The model computes the relevance of past interactions to the current prediction by applying a scaled attention mechanism:

$$\alpha_i = \frac{\exp(e_t^\top W e_i)}{\sum_{j=1}^{t} \exp(e_t^\top W e_j)}, \tag{2}$$

where W is a learnable bilinear projection matrix.

The predicted probability that a learner will answer the next question correctly is given by

$$\hat{p}_{t+1} = \sigma\left(\sum_{i=1}^{t} \alpha_i h_i\right), \tag{3}$$

where h_i is a hidden representation associated with interaction i and $\sigma(\cdot)$ is the sigmoid function. The SAKT model therefore identifies which previously encountered concepts influence the learner's performance at the next step. This selective attention capability makes SAKT suitable for modeling irregular and temporally distant dependencies, which are common in educational data.

Under this model, a knowledge vector is created continuously and it represents the learner profile created by the SAKT model. This is a very necessary vector in personalizing the sequencing of tasks, as two learners with similar test scores can be very different in their strengths or weaknesses in conceptual learning. With SAKT built in, the system is assured of all recommendations conditioned on the actual progression of mastery of the student instead of hypothesized assumptions on the order of learning.

4.2 SBERT Model

Sentence-BERT (SBERT) gives a semantic account of the totality of instructional material. Each content item T of the repository is transformed to an embedding:

$$v = \mathrm{SBERT}(T). \tag{4}$$

These embeddings allow task-task conceptual relationships and the system can measure similarity, can identify prerequisite structure, and predict cognitive difficulty. Estimation of difficulty is calculated by placing every task relative to the centroid of items that a person has mastered. Given v_{mastered}, the semantic difficulty of item q is defined as

$$D(q) = 1 - \frac{v_q \cdot v_{\text{mastered}}}{\|v_q\| \|v_{\text{mastered}}\|}. \tag{5}$$

Higher values of $D(q)$ indicate greater conceptual distance from the learner's current mastery region.

Along with difficulty estimation, SBERT embeddings enable the system to create an organized structure of topics, and recommended tasks do not switch directly to unrelated ideas. Pedagogical ordering is also given through content clustering in such a way that tasks may be ordered in sequence, starting with foundational and culminating with advanced.

SBERT makes sure that the recommendations given by the system in regard to the task are not arbitrary but they are related to the cognitive and semantic intimacy. It allows the model to know the difficulty of an item to a given learner and also gives the semantic basis needed to build useful adaptive learning sequences.

4.3 DQN Model

The Deep Q-Network (DQN) model performs decision-making and task sequencing. At time t, the system forms a composite state

$$s_t = [KS_t,\ D_t,\ E_t], \tag{6}$$

where KS_t is the knowledge-state output of SAKT, D_t contains SBERT-derived difficulty measures, and E_t encodes engagement indicators such as time on task and repeated attempts.

The DQN model chooses the next learning item by computing the action that maximizes the estimated Q-value:

$$a_t = \arg\max_a Q(s_t, a; \theta). \tag{7}$$

After the learner completes the recommended task, the system observes the outcome and generates a reward signal. The Q-network parameters are updated according to the Bellman equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right]. \tag{8}$$

Through this iterative update process, the DQN learns a policy that balances reinforcement of weak concepts with the introduction of new challenges. Over time, it converges to a strategy that maximizes long-term learning gains instead of short-term correctness alone.

The DQN model acts as the core of the personalization engine. It integrates the learner state from SAKT and the content properties from SBERT to compute the optimal next task. This integration turns the system into a fully adaptive learning environment, enabling personalized sequencing based on learned policies rather than manually crafted rules.

4.4 Integrated Workflow

The entire processing process starts when a student tries to complete a task. Depending on the outcome, the SAKT model rewrites the knowledge of the learner. SBERT examines the left-over tasks to assert their semantic and cognitive distance between the current knowledge of the learner. DQN model is then used to select the next best task based on a combination of these signals into one decision that is guided by reinforcement. Once the student tries the suggested item, all models change their states and the process repeats itself. Such a closed-loop system guarantees the dynamism, consistency and sensitivity of personalization to the changing learning process.

5 Experimental Results

5.1 Experimental Environment

All the experiments were performed at a workstation with an Intel Core i9-12900K CPU, 64 GB DDR5 RAM and Nvidia RTX 4090 GPU with 24 GB VRAM. This setup allowed having enough computational resources to train the SAKT learner model, create SBERT embeddings, and execute reinforcement learning episodes that addressed the DQN-based recommendation module. The software environment was composed of Python 3.10, PyTorch 2.2, CUDA 12.1 and HuggingFace Transformers for SBERT. The reinforcement learning experiments were based on Stable-Baselines3 framework and the clustering and statistical evaluations were carried out with Scikit-Learn. All the data preprocessing, logging and model evaluation pipelines were made in a controlled reproducible environment using JupyterLab and Weights Biases for experiment tracking.

The data utilized in the experiments were 1200 curated learning items (collected on introductory mathematics and language courses), and 32,000 student interaction logs (anonymized). The logs had learner identifier, time, question identifier, correctness label, response time and subject metadata. The dataset was split into 80% training data and 20% for evaluation data. The content bank items were preprocessed by text normalization, removal of formatting artifacts, and conversion of content bank item to its respective SBERT embedding.

5.2 Evaluation Methodology

The evaluation of the proposed adaptive learning framework was performed in combination of predictive accuracy measures, semantic quality measures, and reinforcement learning convergence measures. These metrics were chosen because they correspond directly to the functional role of the SAKT, SBERT and DQN models in the system. The SAKT model is designed to estimate learner knowledge progression; thus, the model performance is best measured using probability-based prediction measures such as Accuracy, AUC and Cross Entropy Loss, which is used to validate how well the model anticipates future learner responses. The high-dimensional semantic embeddings of learning materials produced by the SBERT component are suitable for the use of quality metrics like cosine distance and silhouette coefficients for the analysis of how well the semantic structure correlates with observed task difficulty. The DQN model is validated using reward convergence behaviour, which is a function of the ability of the agent to learn an optimal policy of instruction in a given period of time. These evaluation methods form a comprehensive and multidimensional evaluation of the framework that ensures that each computational module is validated based on the intended contribution for which it was designed as part of the adaptive personalization process.

The predictive performance of the SAKT knowledge model is evaluated through Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{9}$$

Area Under the ROC Curve (AUC):

$$\text{AUC} = \int_0^1 TPR(FPR)\, d(FPR), \tag{10}$$

and Cross-Entropy Loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{p}_i) + (1 - y_i)\log(1 - \hat{p}_i)\right]. \tag{11}$$

The semantic consistency of SBERT embeddings is evaluated using the cosine similarity measure:

$$\cos(\theta) = \frac{v_i \cdot v_j}{\|v_i\|\|v_j\|}, \tag{12}$$

and the silhouette coefficient:

$$S = \frac{b(i) - a(i)}{\max(a(i), b(i))}, \tag{13}$$

where $a(i)$ is the mean intra-cluster distance and $b(i)$ is the minimum mean inter-cluster distance.

The learning behaviour of the DQN recommendation agent is assessed using the temporal-difference Bellman update error:

$$\delta_t = r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t), \tag{14}$$

and cumulative episodic reward:

$$R_{\text{episode}} = \sum_{t=1}^{T} r_t. \tag{15}$$

5.3 Analysis of Results

Experimental analysis started with grid-search hyperparameter tuning of all the three models. The aim of this stage was to determine the most stable and high-performing configuration for each of the components before the full-scale testing. The combinations of learning rates, embedding sizes, attention heads, batch sizes and reward discount factors were explored in search for improving play. For SAKT, the search was based on the aspects of embedding dimensions, number of attention heads, and the dropout rates. In the case of SBERT, the search combined pooling strategies and batch sizes. For the DQN agent, several important parameters including learning rate, decay of exploration, update frequency of target network, and replay buffer size were optimized. The ultimate chosen hyperparameters, which were to be gained during the grid-search process, are presented in Table 4.

Table 4: Optimal Hyperparameters Obtained from Grid Search

Model	**Parameter**	**Search Range**	**Optimal Value**
SAKT	Embedding Dimension	{64, 128, 256}	128
SAKT	Attention Heads	{2, 4, 8}	4
SAKT	Dropout Rate	{0.1, 0.2, 0.3}	0.2
SBERT	Pooling Strategy	{mean, max, cls}	mean
SBERT	Fine-tuning Batch Size	{8, 16, 32}	16
DQN	Learning Rate	{1e-5, 1e-4, 5e-4}	1e-4
DQN	Discount Factor (γ)	{0.85, 0.90, 0.95}	0.95
DQN	Exploration Decay	{0.99, 0.995, 0.999}	0.995
DQN	Replay Buffer Size	{5000, 10000, 20000}	10000

After the best hyperparameters were found, the models were tested on the metrics from the previous subsection. The SAKT knowledge-tracing model showed good predictive power in terms of high Accuracy and AUC, which means the self-attention mechanism successfully extracted learning dependencies over time. The content clusters obtained from the semantic embeddings using SBI generated coherent content clusters, as shown by silhouette score and cosine-distance correlation with empirical difficulty. In the meantime, the DQN agent exhibited consistent convergence behaviour with cumulative episodic rewards growing steadily as the policy improved. The quantitative evaluation results of the three components are presented in Table 5.

Table 5: Quantitative Evaluation Results for SAKT, SBERT, and DQN Models

Model	**Metric**	**Result**	**Interpretation**
SAKT	Accuracy	0.78	High correctness prediction
SAKT	AUC	0.84	Strong discrimination ability
SAKT	Cross-Entropy Loss	0.41	Low prediction uncertainty
SBERT	Silhouette Score	0.62	Well-separated content clusters
SBERT	Cosine Difficulty Corr.	0.71	Difficulty aligns with performance
DQN	Avg. Episode Reward	8.1	Stable policy convergence
DQN	Training Convergence	600 episodes	Rapid learning stabilization

On inspecting the results a bit more closely, we can see that there is consistency and mutual reinforcement between the three components. The excellent predictive power of the SAKT model allowed the mastery level of every learner to be estimated reliably and to provide an accurate basis for downstream personalization. The attention mechanism was effective in prioritizing conceptually relevant historical interactions, which enabled SAKT to induce complex dependencies which are missed by simple knowledge tracing methods. As a result, the knowledge-state representation that the DQN agent got was a stable and expressive one.

The clustering result of the SBERT was further used to validate the semantic structure of the content repository. Objectives with historical associations of a greater error rate were found in semantically distant areas of embedding space and indicates that the model reflected cognitive patterns of difficulty besides linguistic resemblance. This is a property that is necessary, since the DQN agent uses SBERT-derived distances to approximate the difficulty level of a task to a particular learner. The high correlation between the cosine difficulty proves that these distances had meaning and were consistent with actual learner performance.

The behaviour of the DQN agent learning process revealed a clear shift from exploring to exploiting. The initial episodes had very unpredictable rewards indicating unstable policy decisions. As the training progressed, the cumulative trend of the reward became more stable and the agent was persistently choosing the tasks that maximized the predicted learning gains. It is typical of structured decision setting to converge around episode 600, and therefore the integration of SAKT and SBERT features allowed the agent to learn to act in an optimal way.

The synergy between the three components is also emphasized by having an integrated cross-model interpretation. The correct knowledge-state vectors of SAKT served as effective signals to the reinforcement learning agent, and the structured semantic representation of SBERT caused the DQN not to provide a sudden and pedagogically unsuitable task suggestion. The net result was a self-paced learning cycle that effectively promoted the smooth progress in the level of difficulty among the learners as the choices of tasks not only solved the conceptual preparedness of the learners but also the engagement pattern.

6 Conclusion

This paper proposed an adaptive learning system that combines the SAKT model of learner knowledge estimation, SBERT model of semantic content representation and a DQN-based policy learner that uses personalized task suggestions. Experimental analyses showed that combining temporal knowledge modelling, high-dimensional representations, and reward-based task sequencing are effective in personalizing higher education and that the technology has good predictive performance, consistent semantic grouping of content, and convergence of reinforcement learning. Although the results are promising, the study is limited because it used a controlled learning dataset, one learning domain and simulated interaction traces, which may make the findings less generalizable. The model should be applied to real classroom deployments, multimodal behavioural signals, and explainable and fairness-sensitive mechanisms that maximize interpretability, equity and robustness in multigenerational leaner populations in the future. Comprehensively, the results indicate the promise of AI-based personalization to promote the adaptive learning processes and enhance student engagement in higher learning institutions.

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