

Deep Learning-Based Hybrid Model for Knowledge Tracing and Personalised E-learning

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Abstract—Personalised learning has emerged as an essential part of modern education systems, demanding intelligent models that can adapt to each learner’s developing knowledge and preferences. Our paper proposes a novel hybrid deep learning framework that utilises sequential modelling using Long Short-Term Memory-based Deep Knowledge Tracing (LSTM-DKT), Self-Attentive Interaction Network for Knowledge Tracing (SAINT), and Variational Autoencoder-based Collaborative Filtering (VAE-CF) to produce personalised learning recommendations. The model combines the strengths of both LSTM and SAINT to predict a learner’s mastery over time, and integrates these predictions into the VAE-CF model to align the learner’s knowledge with their latent content preferences. The integrated architecture employs learning patterns and collaborative filtering to address challenges related to cold start and sparsity in educational data. This hybrid system outperformed the baseline models in both mastery prediction and personalized recommendation tasks. The research shows that cognitive tracing and collaborative filtering significantly enhance the accuracy and relevance of personalised content, providing a strong basis for the development of more flexible and student-centered e-learning platforms.

Index Terms—Personalised Learning, Deep Knowledge Tracing, LSTM, SAINT, Variational Autoencoder, Collaborative Filtering, Recommender System, Adaptive E-Learning

I. INTRODUCTION

The popularity of online education platforms has led to a growing need for personalised learning systems that cater to the unique requirements of each learner. Conventional e-learning systems often follow a one-size-fits-all approach, which can lead to poor outcomes in knowledge acquisition. Furthermore, e-learning and other forms of online and distance education have gained increased importance, especially after the COVID-19 pandemic, which accelerated digital transformation across the education system [1]. Rather than being seen solely as a disruption, the pandemic served as a turning point that highlighted the need for inclusive digital learning tools to bridge the gaps between urban and rural educational settings, in line with the United Nations Sustainable Development Goal 4 (SDG 4). Due to these emerging needs, educators and

students need to adopt learning technologies such as digital tools and platforms to engage with education through diverse new methods [2].

Artificial intelligence (AI) has the potential to significantly enhance e-learning systems by enabling content delivery that responds to the needs of individual learners. Unlike traditional e-learning platforms that present the same material to all students at a given grade level, AI-driven adaptive systems generate specific and targeted content for each learner. Through personalisation, learners can achieve better outcomes, based on individual strengths and areas for improvement [3] [4].

In recent years, significant studies have focused on personalised e-learning, which is based on two primary factors: the first is knowledge tracking, which models the progression of student mastery from interaction histories to predict future performance, and the second aspect involves personalized recommendations, which align content with learners’ skills and comprehension levels [5]. An integrated approach that can suggest content based on skill dependencies and mastery levels can improve learning efficiency and effectiveness when coupled with quality educational resources.

Significant advancements have been made recently in addressing the knowledge tracing problem. An advanced machine learning technique called Deep Learning-based Knowledge Tracing (DLKT) is used to model and forecast students’ knowledge states over time based on their interactions (e.g., answering questions correctly or incorrectly). The DLKT method was first proposed by Piech et al. [6]. These models attempt to predict the probability that a student will correctly respond to a subsequent question by learning sequential patterns from data, usually logs of student interactions. However, it is still unclear how successful DLKT techniques are, and it remains difficult to evaluate and analyse these techniques properly in an online education context [7]. This study employs two representative DLKT methods: (i) LSTM-based DKT, which captures sequential dependencies [8] and

(ii) the transformer-based SAINT model, to capture a student’s evolving knowledge state over time using an encoder and decoder [9], resulting in improved interpretability and prediction accuracy.

A learner’s current knowledge can be traced using knowledge tracing models; however, these models cannot recommend what the learner should study next. In contrast, recommender systems focus on suggesting relevant material but typically lack a deep understanding of individual learning dynamics. Recent advancements in deep learning-based recommender systems, particularly those employing Variational Autoencoder (VAE)-based collaborative filtering models (VAE-CF) [10], have demonstrated significant efficacy in learning latent representations of user-item interactions. However, these systems often operate without incorporating learners’ cognitive processes, which limits their effectiveness in academic contexts where understanding knowledge progression is essential.

This study presents a hybrid deep learning framework that integrates an LSTM-DKT model for modelling sequential learner performance, a Transformer-based SAINT model for contextual encoding of learning sequences, and a VAE-CF model for content recommendation. The proposed methodology enables personalised end-to-end learning by combining knowledge tracing and recommendation into a unified pipeline. This integration allows the system to track a learner’s knowledge and dynamically adapt the next skill to be learned. The contributions of this study are as follows:

- 1) We develop a hybrid architecture that integrates DLKT models such as LSTM-DKT and SAINT with a probabilistic recommendation system VAE-CF.
- 2) We present a deployment architecture for large-scale personalisation in adaptive e-learning systems for practical application.

The remainder of this paper is organised as follows. Section II reviews related work. Section III describes the proposed methodology. Section IV presents the results and discussion. Finally, Section V provides the conclusion and outlines directions for future work.

II. RELATED WORK

We present related work aimed at developing personalised e-learning systems, focusing on two key components: deep knowledge tracing for evaluating learners’ knowledge levels, and deep learning-based recommender systems. A range of methodologies has been explored to enhance these components within the domain of e-learning. Below, we provide an overview of prior studies that have employed machine learning and deep learning techniques for these purposes. These models utilise both supervised and unsupervised learning approaches to predict learner performance.

A. Evolution from Deep Learning to Transformer model in Knowledge Tracing

Knowledge tracing is the process of modelling students’ knowledge mastery over time using data from past learning

interactions, in order to forecast how well they will perform in future interactions. When combined with high-quality learning materials and instruction, such predictive capabilities can enhance student learning and accelerate progress towards personalised education. Research on knowledge tracing has been conducted since the 1990s, and to the best of our knowledge, Corbett and Anderson were the first to evaluate students’ current knowledge of each distinct knowledge component using Bayesian Knowledge Tracing (BKT) [11], which assumes skill independence, lack of memory, and fixed transition parameters. Since then, several attempts have been made to address the knowledge tracing problem, including Item Response Theory (IRT), which estimates student ability and item difficulty [12], and factor analysis-based models [13]; however, these approaches assume linear learning behaviour and lack temporal granularity.

Recently, the rapid advancement of deep neural networks has established DLKT models as the standard framework for simulating students’ mastery of knowledge components. Table I categorises DLKT methods into deep sequential models (DKT), memory-augmented models (DKVMN), graph-based models (GKT), and attention-based models (SAKT, SAINT) [14]. With the growing interest in deep learning, DLKT models [15] have developed significantly, with the LSTM-based approach being one of the first to represent sequential student learning activity. This approach was able to capture temporal dependencies in student responses, outperforming more conventional techniques such as BKT and IRT.

Similarly, DKVMN creates a dynamic value matrix to update the student’s knowledge state and a static key matrix to store the relationships between various knowledge components, but it may lack sufficient capacity to represent complex knowledge structures [16]. Further improvements were made with the GKT model, which utilises graph neural networks (GNNs) to better capture student learning behaviours and concept relationships as a graph. However, it is not inherently sequential, and temporal logic must be encoded manually [17].

However, attention-based knowledge tracing models such as SAKT and SAINT are regarded as superior because they overcome the drawbacks of previous models (LSTM-DKT, DKVMN, and GKT) and offer flexibility, efficiency, and state-of-the-art performance across multiple datasets (e.g., ASSISTments, EdNet, Junyi). These are transformer-based models that provide improved parallelism and better long-range dependency modelling through self-attention mechanisms. In 2019, Pandey and Karypis [18] introduced SAKT, which allowed the model to focus on the most relevant past responses, improving both training efficiency and predictive accuracy. However, SAKT’s reliance on a fixed-length history limited its ability to capture long-range dependencies. To address these limitations, the SAINT model [19] was introduced. It employs positional encoding and relative temporal information to represent global attention across a student’s complete interaction sequence. SAINT significantly outperformed earlier models in predictive accuracy on large-scale knowledge tracing benchmark datasets, owing to its ability to model long-term dependencies

TABLE I
COMPARISON OF TRADITIONAL AND DLKT MODELS

Model	Architecture	Temporal Modeling	Skill Awareness	Attention Mechanism	Performance
IRT	Probabilistic Model	None	Explicit	No	Moderate
BKT	Hidden Markov Model	Basic	Explicit	No	Low
DKT	LSTM (RNN-based)	Strong	Implicit	No	High
DKVMN	Key-Value Memory Network + RNN	Strong	Implicit	Yes	High
GKT	GNN + Student-Skill Graph	Variable	Implicit	Yes	High
SAKT	Self-Attention over History	Short-Term	Implicit	Yes	High
SAINT	Full Transformer Encoder	Long-Term	Implicit	Yes	State-of-the-Art

and capture more nuanced contextual information.

B. Deep Learning-Based Recommender Systems

Recommender systems are becoming an essential component of personalised learning environments, as they enable content to be delivered in a manner that adapts to the needs of each learner. Traditional collaborative filtering (CF) techniques such as user based CF, item based CF, and matrix factorisation face challenges in addressing the cold start problem, interaction sparsity, and the absence of mechanisms to account for item difficulty and learning progression. As a result, these methods often yield suboptimal performance in educational settings due to limited interaction data and insufficient contextual awareness [20].

To overcome these limitations, deep learning based recommender systems have been developed, utilising non-linear representations and probabilistic modelling to improve recommendation performance. Similarly, Neural Collaborative Filtering (NCF) [21] extends matrix factorisation by replacing dot-product similarity with multi-layer perceptrons.

Content-based filtering (CBF) [22], which is frequently used in education to suggest resources based on metadata such as topic and difficulty, performs well in the early stages of learning. However, it is unable to capture latent student behaviours and collaborative signals. In contrast, VAE-CF provides a more comprehensive personalisation approach by combining collaborative signals with content features. It is effective in handling robust latent factors even in sparse and high-dimensional user-item interaction data within personalised learning systems. VAE-CF learns complex non-linear correlations through deep probabilistic encoding and decoding processes, enabling improved generalisation for cold start learners and underrepresented items. Overall, VAE-CF [23] offers a strong solution for integration with deep knowledge tracing models in adaptive learning systems, as it achieves a balance between expressiveness, scalability, and generalisation.

III. PROPOSED METHODOLOGY

This section outlines the proposed hybrid framework, which integrates an LSTM-DKT model to capture sequential learning patterns, a SAINT transformer-based knowledge tracing model to enhance context awareness through self-attention mechanisms, and a VAE-CF system to deliver personalised e-learning content. The objective is to accurately determine the evolving knowledge state of each learner and recommend

content aligned with their interests and knowledge gaps. The proposed hybrid model consists of learner interaction data, a knowledge tracing model, and personalised recommendations via VAE-CF, as illustrated in Fig. 1.

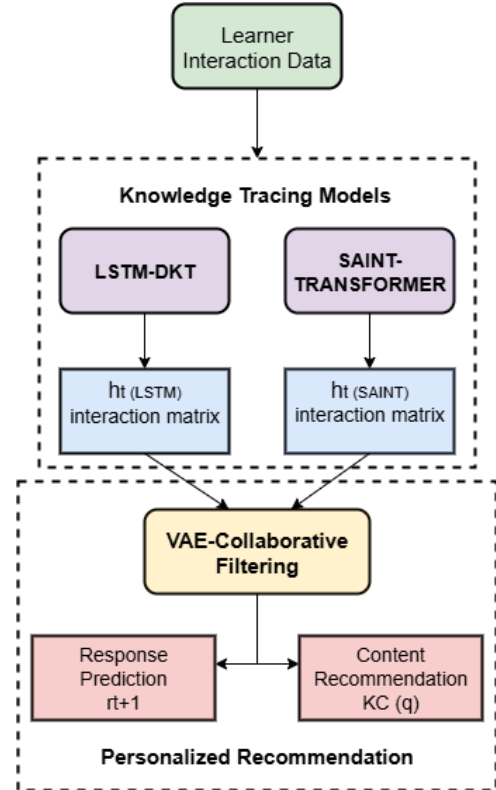


Fig. 1. Hybrid Model for Personalised Recommendation

A. Learner Interaction Data

The e-learning platform generates learner interaction data whenever a student engages with it. The learner data module is constructed using the ASSISTments 2017 dataset [24], a widely used benchmark in educational data mining and knowledge tracing research. This dataset includes anonymised interaction logs of students using an intelligent tutoring system during real learning sessions to solve mathematics problems. Each interaction record contains information such as student ID, timestamp, problem ID, skill tag (knowledge component), and correctness (correct or incorrect).

Input Representation: The dataset used in this study has been preprocessed to extract meaningful student interaction

sequences, as shown in Fig. 2, which are then fed into the knowledge tracing models. To preserve learning progression over time, the sequences are arranged temporally for each learner. These sequences are converted into fixed-length input vectors that represent the problem ID, skill ID, and response outcome. This data is used by the LSTM-DKT and SAINT models to predict whether a student will answer the next problem correctly based on their past skill performance. The input data consists of the following components:

- the set of learners, $U = \{u_1, u_2, \dots, u_N\}$
- the set of skills, $S = \{s_1, s_2, \dots, s_N\}$
- the set of questions, $Q = \{q_1, q_2, \dots, q_M\}$
- the sequence of interaction for each learner, $I_u = \{(q_1, r_1), (q_2, r_2) \dots, (q_T, r_T)\}$, where r_T denoting correctness.

B. Knowledge Tracing Model

1) LSTM-based Deep Knowledge Tracing (LSTM-DKT):

The LSTM-DKT represents the sequential nature of learner's learning activities over time. A sequence of student responses is processed, and they are mapped to a latent representation of the learner's changing knowledge state in order to capture the temporal dependencies found in learner interactions. Each learner interaction I_u at each time step is encoded into a fixed-length input vector that indicates the skill attempted and whether the response was correct. The LSTM network receives this input sequence and maintains a hidden state h_t , which encodes the progression of the learner's knowledge over time, as defined in Equation (1).

$$h_t = \text{LSTM}(I_u, h_{t-1}) \quad (1)$$

The learner's probability of correctly answering the next question/skill is predicted using a fully connected layer with a sigmoid activation, as shown in Equation (2). Optimal results were obtained with a learning rate of 0.001 (Adam optimizer), hidden size of 256, and dropout of 0.3 to mitigate overfitting.

$$y_{t+1} = \sigma(Wh_t + b) \quad (2)$$

2) *SAINT Transformer-based Model*: SAINT is an advanced transformer-based adaptation specifically designed for knowledge tracing. This approach utilises self-attention mechanisms to effectively capture long-range dependencies within student interaction sequences, resulting in improved performance, particularly on sparse data. It employs an encoder-decoder structure to process sequences of problem-response pairs. The encoder encodes a sequence of exercise embeddings and passes the resulting representations to the decoder. Both the encoder and decoder consist of multi-head attention networks, which serve as the core components of SAINT, supported by feed-forward layers with ReLU activation to produce the final predictions. This architecture enhances learner knowledge representation, particularly in the presence of complex skill dependencies. The final prediction at each time step is computed as shown in Equation (3).

$$h_t = \text{MultiHeadAttention}(Q, K, V) \quad (3)$$

where Q, K and V are the projected queries, keys and values, respectively. The performance of the model was improved by utilizing attention heads to capture various relational patterns among interactions, an embedding size of 256 to balance computational efficiency, a dropout rate of 0.2 to prevent overfitting, and a learning rate of 0.001, ensuring that the model achieves high accuracy.

C. Preference Learning via Variational Autoencoder Collaborative Filtering (VAE-CF)

The VAE-CF model acquires latent embeddings for both learners and learning items. This module uses implicit feedback to discover a latent representation of students' interests, allowing for personalised learning content recommendations. It includes a sparse user-item matrix that contains previous learner-content interactions. The encoder translates learner-item interaction data X_u into a latent space vector z_u . The decoder then generates predicted interaction scores for previously unobserved content, as shown in Equation (4).

$$X_u = \text{softmax}(Wz_u + b) \quad (4)$$

To improve the quality of recommendations, hyperparameter tuning was performed on key parameters of the VAE-CF model. Specifically, the latent dimension size of 100, learning rate of 0.002, batch size of 256, and dropout of 0.3 was tuned to optimize training efficiency, mitigate overfitting and provide the best trade-off between accuracy and generalization.

D. Hybrid Model for Personalised Recommendation

The outputs generated by the LSTM and SAINT models are used to assess each learner's mastery level across specific skills or concepts. These mastery predictions are then passed to the VAE-CF module, where they are combined with latent user-item interaction embeddings to generate personalised content recommendations. The final output evaluates learning resources to address knowledge gaps, and sustain learner engagement. This hybrid system overcomes the limitations of standalone knowledge tracing and collaborative filtering models by supporting knowledge retention, enabling adaptive learning pathways, and improving learner autonomy.

TABLE II
PERFORMANCE OF KNOWLEDGE TRACING & HYBRID MODELS

Model Variant	Accuracy	Recall	VAE-CF Personalised Output (Recall@10)
LSTM-DKT	0.792	0.731	-
SAINT	0.829	0.752	-
LSTM-DKT + VAE-CF	0.824	0.773	0.661
SAINT + VAE-CF	0.838	0.801	0.685

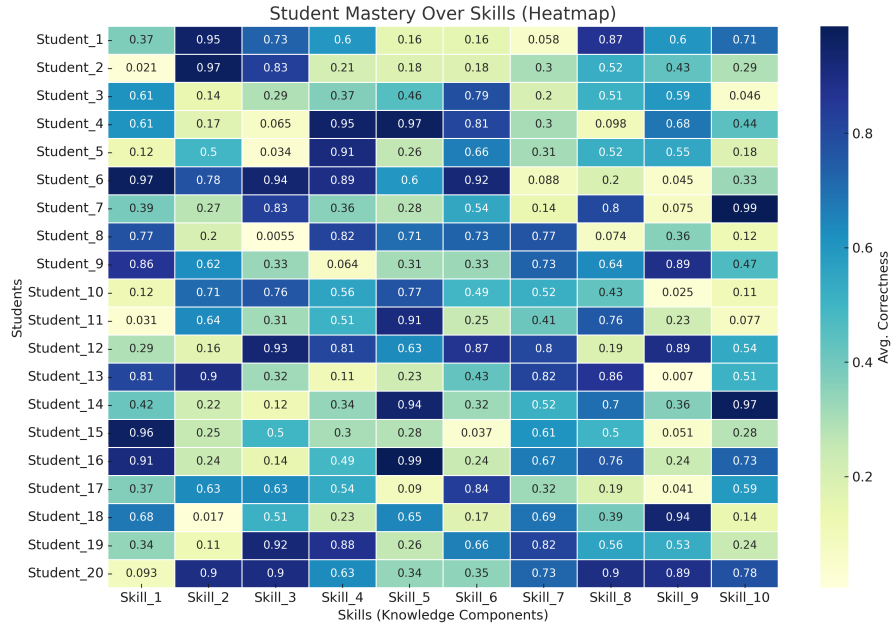


Fig. 2. Student-skill interactions (Knowledge Tracing)

IV. RESULTS AND DISCUSSION

This section evaluates the proposed hybrid model, which integrates LSTM-DKT and SAINT with VAE-CF to generate recommendations based on both knowledge and learner preferences. The model was evaluated using the ASSISTments2017 dataset [24], a widely used benchmark in knowledge tracing research. Performance was assessed using two primary metrics for prediction—accuracy and recall—and recall@10 for recommendation effectiveness. Table II presents a comparison between the baseline models and the proposed hybrid system.

The LSTM-DKT model achieved an accuracy of 0.792 and a recall of 0.731, demonstrating its ability to capture sequential learner patterns. In contrast, SAINT outperformed LSTM-DKT with an accuracy of 0.829 and a recall of 0.752, owing to its attention mechanism, which more effectively models contextual relationships in student interactions.

Although the VAE-CF model is not explicitly designed for knowledge tracing, it performed reasonably well on recommendation metrics, achieving a recall@10 of 0.661 when combined with LSTM-DKT and 0.685 when combined with SAINT. The results clearly show that the hybrid model SAINT + VAE-CF outperforms LSTM-DKT + VAE-CF across all three evaluation metrics. Specifically, SAINT + VAE-CF achieved an accuracy of 0.838 and a recall of 0.801, compared to 0.824 and 0.773 for LSTM-DKT + VAE-CF, respectively. These improvements indicate that SAINT’s self-attention mechanism more effectively captures long-range dependencies in learner interactions, thereby enhancing prediction accuracy.

The proposed hybrid framework offers a more comprehensive view of learner performance than conventional models, which typically focus solely on personalised recommenda-

tions. This integration is particularly beneficial in scenarios involving sparse or imbalanced learner interaction data, as the combination of sequential learning and probabilistic encoding helps to reduce noise and improve generalisation. Furthermore, the observed improvement in personalisation demonstrates that the hybrid model effectively prioritises pedagogically relevant content, which is critical for supporting learner progress.

V. RISK AND CHALLENGES

Despite the promising performance of the proposed hybrid model that integrates knowledge tracing with personalized recommendation, several risks and challenges remain for its deployment in real-world educational environments.

- 1) **Scalability and System Performance:** A key challenge is scaling the hybrid model to support large learner cohorts across diverse institutions. Integrating deep learning-based knowledge tracing (LSTM, SAINT) with VAE-CF intensifies computational demands, raising concerns about latency, memory, and responsiveness under high user loads. Prior work emphasizes the role of system optimization and distributed infrastructures for scalable learning analytics [25]. Hence, efficient computation and strong load balancing are crucial to sustain real-world performance.
- 2) **User Interaction and Feedback Mechanisms:** Personalization is driven by mastery predictions, but responsive feedback and user-friendly interfaces are necessary for learner adoption. Prior research has highlighted the importance of user feedback loops in validating adaptive learning systems and enhancing learner trust and engagement [26]. Clear recommendations and learning pathways must be communicated.

- 3) **Ethical and Responsible AI Considerations:** AI-driven personalization in education raises critical ethical concerns. Protecting learner data privacy and security is essential, given the sensitivity of performance and behavioral information. Risks of algorithmic bias may lead to unequal recommendations across demographic groups [27]. Ensuring transparency, fairness, and accountability is vital, with explainability and bias mitigation strategies enhancing trust and credibility. Clear ethical guidelines are therefore necessary to align with best practices in AI and educational technology.

VI. CONCLUSION AND FUTURE WORK

This study introduced a deep learning-based hybrid framework that integrates sequential (LSTM-DKT) and attention-driven (SAINT) knowledge tracing models with a VAE-CF recommender to deliver personalized e-learning. By modeling both learners' evolving knowledge states and latent content preferences, the framework enables dynamic and individualized recommendations. Results show that SAINT + VAE-CF outperforms LSTM-DKT + VAE-CF, highlighting the effectiveness of attention mechanisms in improving knowledge tracing and personalization. The hybrid approach also addresses challenges such as handling sparse learner-content interactions, mitigating cold-start issues, and ensuring better alignment of content with learner progress. Future work will focus on incorporating multimodal data sources (e.g., eye tracking and facial expressions) to capture richer learner context, including motivation and engagement. Broader validation with diverse datasets and learner demographics will strengthen the model's generalizability. Additionally, deploying the framework in real-world educational platforms will enable evaluation of practical effectiveness, not only through algorithmic performance but also in terms of learning gains, user satisfaction, and engagement. Active learning strategies and real-time feedback loops represent further opportunities to enhance adaptability and responsiveness.

REFERENCES

- [1] N. K. Dicheva, I. U. Rehman, A. Anwar, M. M. Nasralla, L. Husamaldin, and S. Aleshaiker, "Digital transformation in nursing education: A systematic review on computer-aided nursing education pedagogies, recent advancements and outlook on the post-covid-19 era," *IEEE Access*, vol. 11, pp. 135 659–135 695, 2023.
- [2] A. Selvaraj, V. Radhin, N. Benson, A. J. Mathew *et al.*, "Effect of pandemic based online education on teaching and learning system," *International journal of educational development*, vol. 85, p. 102444, 2021.
- [3] A. Anwar, I. U. Rehman, M. M. Nasralla, S. B. A. Khattak, and N. Khilji, "Emotions matter: A systematic review and meta-analysis of the detection and classification of students' emotions in stem during online learning," *Education Sciences*, vol. 13, no. 9, p. 914, 2023.
- [4] J. Pordoy, H. Farman, N. Dicheva, A. Anwar, M. M. Nasralla, N. Khilji, and I. U. Rehman, "Multi-frame transfer learning framework for facial emotion recognition in e-learning contexts," *IEEE Access*, 2024.
- [5] G. Abdelrahman, Q. Wang, and B. Nunes, "Knowledge tracing: A survey," *ACM Computing Surveys*, vol. 55, no. 11, pp. 1–37, 2023.
- [6] C. Piech, J. Bassen, J. Huang *et al.*, "Deep knowledge tracing," *Advances in neural information processing systems*, vol. 28, 2015.
- [7] M. Murtaza, Y. Ahmed, J. A. Shamsi, F. Sherwani, and M. Usman, "Ai-based personalized e-learning systems: Issues, challenges, and solutions," *IEEE access*, vol. 10, pp. 81 323–81 342, 2022.
- [8] J. Mandlazi, A. Jadhav, and R. Ajoodha, "Evaluating deep sequential knowledge tracing models for predicting student performance," in *2021 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*. IEEE, 2021, pp. 1–6.
- [9] Y. Choi, Y. Lee, J. Cho, J. Baek, B. Kim, Y. Cha, D. Shin, C. Bae, and J. Heo, "Towards an appropriate query, key, and value computation for knowledge tracing," in *Proceedings of the seventh ACM conference on learning@ scale*, 2020, pp. 341–344.
- [10] S. Liang, Z. Pan, W. Liu, J. Yin, and M. De Rijke, "A survey on variational autoencoders in recommender systems," *ACM Computing Surveys*, vol. 56, no. 10, pp. 1–40, 2024.
- [11] S. Shen, Q. Liu, Z. Huang, Y. Zheng, M. Yin, M. Wang, and E. Chen, "A survey of knowledge tracing: Models, variants, and applications," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1858–1879, 2024.
- [12] Y. Su, Z. Cheng, P. Luo, J. Wu, L. Zhang, Q. Liu, and S. Wang, "Time-and-concept enhanced deep multidimensional item response theory for interpretable knowledge tracing," *Knowledge-Based Systems*, vol. 218, p. 106819, 2021.
- [13] S. Pu, G. Converse, and Y. Huang, "Deep performance factors analysis for knowledge tracing," in *International Conference on Artificial Intelligence in Education*. Springer, 2021, pp. 331–341.
- [14] Z. Liu, Q. Liu, J. Chen, S. Huang, J. Tang, and W. Luo, "pykt: a python library to benchmark deep learning based knowledge tracing models," *Advances in Neural Information Processing Systems*, vol. 35, pp. 18 542–18 555, 2022.
- [15] Z. Liu, T. Guo, Q. Liang, M. Hou, B. Zhan, J. Tang, W. Luo, and J. Weng, "Deep learning based knowledge tracing: A review, a tool and empirical studies," *IEEE Transactions on Knowledge and Data Engineering*, 2025.
- [16] J. Zhang, X. Shi, I. King, and D.-Y. Yeung, "Dynamic key-value memory networks for knowledge tracing," in *Proceedings of the 26th international conference on World Wide Web*, 2017, pp. 765–774.
- [17] H. Nakagawa, Y. Iwasawa, and Y. Matsuo, "Graph-based knowledge tracing: modeling student proficiency using graph neural network," in *IEEE/WIC/aCM international conference on web intelligence*, 2019, pp. 156–163.
- [18] S. Pandey and G. Karypis, "A self-attentive model for knowledge tracing," *arXiv preprint arXiv:1907.06837*, 2019.
- [19] A. R. Hegde, S. Akash, C. Adithya, B. Vaishnavi, and C. Hegde, "Enhanced transformer: Knowledge tracing with incorporation of temporal features," in *2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, vol. 2. IEEE, 2024, pp. 1–6.
- [20] D. Gm, R. Goudar, A. A. Kulkarni, V. N. Rathod, and G. S. Hukkeri, "A digital recommendation system for personalized learning to enhance online education: A review," *IEEE Access*, vol. 12, pp. 34 019–34 041, 2024.
- [21] K. Surya, C. Suganthini, I. Nandhini *et al.*, "Neural matrix factorization and collaborative filtering: A hybrid approach to personalized recommendation," in *2025 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)*. IEEE, 2025, pp. 1–6.
- [22] S. R. Goudar and G. Shidaganti, "Multi-parameter based educational recommendation system for online courses: A content based filtering approach," in *2023 International Conference on Network, Multimedia and Information Technology (NMITCON)*. IEEE, 2023, pp. 1–7.
- [23] S. Vishnu Shankar, S. Naffees Gowsar, and M. Manjubala, "Variational autoencoders (vae)," in *Revolution with Generative AI: Trends and Techniques*. Springer, 2025, pp. 43–64.
- [24] ASSISTments Data Mining Competition, "Assistments 2017 dataset," <https://sites.google.com/view/assistmentsdatamining/dataset>, 2017, accessed: 2025-07-19.
- [25] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM computing surveys (CSUR)*, vol. 52, no. 1, pp. 1–38, 2019.
- [26] F. Ouyang and L. Zhang, "Ai-driven learning analytics applications and tools in computer-supported collaborative learning: A systematic review," *Educational Research Review*, vol. 44, p. 100616, 2024.
- [27] P. Elantheraiyan, K. Priya, R. Gamadia, M. M. Abdulhasan, B. S. Z. Abood, and A. Al-Khalidi, "Ethical design and implementation of ai in the field of learning and education: Symmetry learning technique," in *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*. IEEE, 2024, pp. 1144–1148.