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Comparative Evaluation of Adaptive Learning Models for Trustworthy Personalized Education

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ABSTRACT

Adaptive learning systems (ALSs) aim to personalize education by adjusting content and learning pathways in response to learner performance and behavior. This study conducts a comparative evaluation of four widely adopted adaptive learning models: Item Response Theory (IRT), Bayesian Networks (BN), Collaborative Filtering (CF), and Reinforcement Learning (RL). The evaluation integrates conceptual analysis and empirical simulation, using the large-scale EdNet dataset comprising over 131 million learner interactions. Each model was implemented in Python and assessed with standard metrics, including accuracy, precision, recall, and F1-score, with class imbalance addressed through SMOTE. Results show that RL consistently achieves the strongest performance across personalization accuracy, adaptability, and responsiveness to learner feedback, particularly under balanced conditions. BN closely follows, offering robust predictive accuracy alongside interpretability and cognitive modelling. CF shows moderate effectiveness, with improvements under SMOTE but limited adaptability in sparse or dynamic environments. IRT consistently performs lowest, maintaining value primarily in assessment contexts. Based on these findings, the study proposes a hybrid RL–BN framework, combining RL's dynamic personalization with BN's interpretability to create transparent, scalable, and pedagogically grounded ALSs. The results contribute evidence-based guidance for educators and developers in selecting and integrating adaptive learning models to meet diverse learner and institutional needs.

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INTRODUCTION

Personalised Learning (PL) in smart education adapts educational experiences to individual learners' abilities, preferences, and learning styles. Unlike traditional instruction with uniform content and pacing, PL emphasises learner-centric approaches, active participation, and continuous adaptation to evolving needs (Adewale et al., 2022; (Alshmrany, 2022). Adaptive learning systems (ALSs) support PL by automatically adjusting content, sequence, and difficulty based on real-time learner data, including interaction history, assessment performance, and behavioural patterns (Alshmrany, 2022), Studies report strong demand for adaptive learning in digital education and large online platforms, where many learners struggle to select suitable content and maintain persistence (Adewale et al., 2022; Alshmrany, 2022). Evidence indicates that adaptive systems can increase engagement, improve achievement, and enhance learning outcomes, including higher test performance, better course completion rates, and improved learner satisfaction increases when instructional paths and feedback are tailored to individual learner needs (Adewale et al., 2022; Amin et al., 2023; Bock et al., 2021). Central to adaptive

learning systems (ALSs) is learner modelling, which captures learners' cognitive, behavioural, and emotional characteristics. Learner modelling encompasses psychometric estimation of ability, sequential tracking of knowledge acquisition, learning style detection, cognitive load estimation, and the incorporation of demographic and contextual features (Alshmrany, 2022; Chen et al., 2023; Essa et al., 2023; Pelánek, 2024; Park et al., 2023; Tong et al., 2025). Artificial intelligence and machine learning provide the algorithmic foundation for adaptive learning systems, with algorithmic choices playing a critical role in determining system effectiveness. These approaches include Item Response Theory (IRT) and computerized adaptive testing (CAT) (Bock et al., 2021; Park et al., 2023), Bayesian Networks (Desmarais et al., 2005; Zheng, 2025), collaborative filtering techniques (Chornous et al., 2021; Obeng et al., 2024), sequential and deep learning models (Chen et al., 2023; Safarov et al., 2023; Tong et al., 2025), and reinforcement learning for adaptive learning path selection (Amin et al., 2023; Mon et al., 2023; Luo et al., 2025). Adaptive assessment mechanisms dynamically select learning tasks that align with learner proficiency using frameworks such as IRT, Knowledge Space Theory, and Bayesian Knowledge Tracing (Bock et al., 2021; Park et al., 2023). Furthermore, personalised recommendation systems support learning path generation, course recommendation, and exercise allocation, commonly leveraging collaborative filtering, content-based, hybrid, and knowledge-based recommendation approaches (Adewale et al., 2022; Dai et al., 2023; Ma et al., 2023; Wei et al., 2022).

Despite notable progress in adaptive learning systems, several challenges persist, including cold start, data sparsity, scalability, cognitive overload, data privacy concerns, algorithmic bias, limited model interpretability, and misalignment with curricular objectives (Adewale et al., 2022; Alshmrany, 2022; Amin et al., 2023; Chen et al., 2023; Elegbeleye et al., 2022; Essa et al., 2023; Pal et al., 2025; Park et al., 2023; Obeng et al., 2024). Evaluation of adaptive learning systems typically relies on predictive accuracy, ranking consistency, measured learning outcomes, diversity of recommended learning paths, and user satisfaction metrics (Chen et al., 2023; Dai et al., 2023; Essa et al., 2023; Ma et al., 2023; Park et al., 2023; Tong et al., 2025). The effectiveness of adaptive learning systems further depends on dynamic adaptation mechanisms that continuously adjust instructional paths in real time based on learner interactions and performance, supported by algorithmic foundations including supervised and unsupervised learning, reinforcement learning, deep learning models, and Bayesian networks (Adewale et al., 2022; Amin et al., 2023; Mon et al., 2023). Applications of adaptive learning systems span higher education, specialised domains such as drama education, and fully online learning environments, thereby necessitating rigorous methodological design and sufficient computational resources to ensure effective integration and scalability (Adewale et al., 2022; Wang et al., 2025).

While adaptive learning systems (ALSs) are widely accepted, no single model is universally suitable for addressing the diversity of learners' styles and learning patterns. Existing literature reports fragmented findings, with many studies evaluating adaptive models in isolation using heterogeneous datasets, evaluation metrics, and experimental settings (Essa et al., 2023; Mon et al., 2023; Gligorea et al., 2023). For example, Item Response Theory (IRT) is extensively employed for personalised assessment due to its strong psychometric foundations but exhibits limited real-time responsiveness to evolving learner behaviours (Bock et al., 2021; Park et al., 2023), whereas reinforcement learning supports continuous adaptation of instructional strategies but raises challenges related to model interpretability, computational complexity, and high data requirements (Amin et al., 2023; Mon et al., 2023; Luo et al., 2025). Moreover, many adaptive learning systems are implemented without explicit guidance linking model selection to instructional design principles, system constraints, or learner heterogeneity, thereby increasing the risk of learner disengagement and ethical concerns related to data transparency, bias, and fairness (Elegbeleye et al., 2022; Obeng et al., 2024; Pal et al., 2025).

In response to these gaps, the present study adopts a dual approach comprising a comparative literature review and an empirical evaluation of four widely used adaptive learning models: Item Response Theory, Bayesian Networks, reinforcement learning, and collaborative filtering. Each model is systematically examined with respect to personalisation accuracy, real-

time adaptability, cognitive and knowledge modelling capability, learning outcome prediction, data requirements, and explainability. Through this comprehensive analysis, the study contributes to an evidence-based framework to support informed decision-making in the selection and deployment of adaptive learning models across diverse educational contexts.

The remaining parts of the paper are structured as follows: Section 2 presents the related work; Section 3 discusses the methodology; Section 4 presents the results and discussions, while Section 5 concludes the paper.

RELATED WORK

In adaptive learning, accurate models of learner knowledge are fundamental to effective instructional adaptation. Item Response Theory (IRT) enables precise estimation of learner ability and item difficulty and forms the basis of computerized adaptive testing (CAT), which reduces assessment length while maintaining measurement accuracy (Bock et al., 2021; Park et al., 2023). Bayesian networks extend this modelling capability by explicitly representing uncertainty and probabilistic dependencies among knowledge components, thereby enabling adaptive systems to adjust learning paths dynamically using both historical and real-time learner data (Desmarais et al., 2005; Dai et al., 2023; Zheng, 2025). More recent advances in sequential knowledge tracing and attentive encoder-based models capture the temporal evolution of learner knowledge more effectively, addressing the representational limitations of earlier recurrent architectures (Chen et al., 2023; Safarov et al., 2023; Tong et al., 2025). Collectively, these cognitive modelling approaches provide a robust foundation for delivering personalized instructional content that is closely aligned with individual learner proficiency levels.

Studies have demonstrated that reinforcement learning (RL) and deep reinforcement learning (DRL) can optimize learning sequences by formulating content selection as a sequential decision-making problem (Amin et al., 2023; Mon et al., 2023; Yang et al., 2024). Model-free DRL approaches, such as deep Q-learning, enable data-driven adaptation without requiring predefined transition models, while neural-network-based transition model estimators can further enhance performance in scenarios characterized by limited or sparse data (Yang et al., 2024; Luo et al., 2025). Collectively, these techniques support the development of adaptive learning systems that continuously and responsively adjust instructional strategies in accordance with learner progress and interaction patterns.

Collaborative filtering (CF) leverages patterns in peer behavior to recommend learning materials, employing user-based, item-based, and hybrid approaches to mitigate cold start issues and data sparsity (Chornous et al., 2021; Dai et al., 2023; Obeng et al., 2024; Pal et al., 2025; Tong et al., 2025). Advanced CF models incorporate multi-dimensional data, including temporal and contextual information, to provide more precise recommendations (Chen et al., 2023). Hybrid and modular implementations within learning platforms further support scalable personalization and seamless integration with other adaptive components (Pal et al., 2025). Additionally, graph-based models enhance recommendation quality by capturing interaction networks and hierarchical relationships among learning concepts (Liu et al., 2025; Liu, 2024). Human–computer interaction (HCI) frameworks contribute to improved personalization by integrating learner feedback and interface considerations into adaptive learning systems (Alshmrany, 2022).

Reinforcement learning (RL)–based path planning conceptualizes learning activity selection as a sequential decision-making process, with states, actions, and rewards defined according to instructional content and learner performance (Mon et al., 2023; Yang et al., 2024). Attentive knowledge tracing and hierarchical skill models further optimize next-step recommendations, enhancing both learner mastery and engagement (Essa et al., 2023; Yang et al., 2024). Deep reinforcement learning (DRL) policies strengthen sequential decision-making capabilities, though challenges persist regarding model interpretability and stability, particularly in multi-task learning scenarios (Amin et al., 2023).

Adaptive learning systems incorporate learning style models, such as the Felder–Silverman Learning Style Model (FSLSM), and detect learner styles using behavioral data through hidden Markov models or supervised classifiers (Amin et al., 2023; Desmarais et al., 2005; Pal et al., 2025). Cognitive load estimation further informs adjustments to task difficulty, ensuring learners maintain a manageable effort while making progress (Chen et al., 2023; Park et al., 2023). Together, these approaches enable balanced personalization that considers both learner preferences and workload, enhancing engagement and learning outcomes.

Modular and interoperable components facilitate integration into learning management systems (LMSs). These tools include path planners, Bayesian network–based recommendation engines, engagement monitors, and plugins that support visualization and extensibility (Dai et al., 2023). Large-scale adaptive learning platforms further leverage natural language processing, sentiment analysis, and curriculum structuring to optimize course selection and enhance learner enrollment and satisfaction (Alshmrany, 2022).

System evaluation commonly employs metrics such as mean absolute error (MAE), root mean square error (RMSE), precision, recall, F1 score, AUROC, and Kendall rank coefficients to quantify predictive and ranking performance (Chen et al., 2023; Essa et al., 2023; Ma et al., 2023; Tong et al., 2025). Reported benefits of adaptive learning systems include improved learner performance, higher engagement, and the delivery of diverse yet effective learning paths (Chornous et al., 2021; Choi et al., 2020; Ma et al., 2023). Additionally, robustness and the contribution of individual modules are often assessed through cross-validation across learners and items, as well as ablation studies (Ma et al., 2023; Tong et al., 2025).

Several studies have highlighted persistent challenges in adaptive learning systems (ALSs). Cold start problems are commonly addressed through the use of side information, learner intention analysis, and hybrid psychometric-machine learning models (Park et al., 2023; Dai et al., 2023; Pal et al., 2025). Issues related to data sparsity and scalability motivate the adoption of modular and hybrid system designs (Dai et al., 2023; Pal et al., 2025). Furthermore, privacy, bias, and transparency remain critical considerations, particularly as complex models such as deep reinforcement learning and Bayesian networks often function as "black boxes" (Adewale et al., 2022; Park et al., 2023; Amin et al., 2023; Chen et al., 2023). Consequently, algorithm selection must carefully balance technical performance, interpretability, and pedagogical alignment to maximize learning outcomes.

Table 1. Comparative analysis of adaptive learning algorithms

Algorithm	Mechanism	Strengths	Limitations	Typical Use Cases	Focus
IRT / CAT	Models learner ability and item difficulty; selects items adaptively	High precision; reduces test length; supports information sharing across learners	Degrades with cold start or uncalibrated items; assumes probabilistic ability model	Standardised testing, adaptive assessments, performance prediction	Assessment
BNs	Probabilistic modelling of dependencies among learner traits and content	Handles uncertainty; supports personalised path selection; flexible for real-time updates	Complex model design; requires data; interpretability can be challenging	Adaptive assessment, learning path recommendation, cognitive/affective modelling	Both
CF / Hybrid CF	Predicts preferences from similar learners/items; hybrids	Mitigates cold start; captures learner behaviour;	Data sparsity; cold start for new learners/items; temporal	Course recommendation, content personalisation, adaptive	Recommendation

Algorithm	Mechanism	Strengths	Limitations	Typical Use Cases	Focus
	integrate content signals	scalable and modular	changes not always captured	learning pathways	
Sequential / Deep Models	Captures temporal patterns; uses attentive encoders, deep knowledge tracing	Tracks knowledge evolution; supports cognitive load estimation; improves prediction and recommendation	High data requirements; computational complexity; can be "black box"	Knowledge tracing, personalised path generation, outcome prediction	Both
RL / DRL	Optimises learning sequences via reward-based feedback; model-free handles unknown transitions	Real-time adaptivity; sequential decision-making; hierarchical skill modelling	Needs large interaction datasets; policy interpretability is low; multi-task training may not always improve results	Learning path optimisation, adaptive task recommendation, ITS	Both
Elo Rating Algorithm	Iteratively updates learner ability and item difficulty after each attempt	Fast; inexpensive; simple	Oversimplified; limited capture of complex learning dynamics	Quick adaptive assessments, practice test generation	Assessment

As shown in Table 1 and Fig. 1, the analysis reveals distinct focuses and characteristics among adaptive learning models. IRT, CAT, and BN are mainly used for accurate assessment and learner modelling, while CF, hybrid CF, and deep sequential models focus on personalized content recommendation. RL and DRL integrate both assessment and sequencing by dynamically optimizing learning paths. Regarding adaptivity, RL/DRL and BN allow continuous updating based on learner performance, whereas IRT and CF generally rely on historical or batch data unless extended with online mechanisms. However, data requirements differ, with sequential/deep models and DRL requiring larger datasets compared with IRT, BN, or Elo-based methods. In terms of interpretability, IRT and CAT provide straightforward outputs, BN is interpretable probabilistically, and deep models and DRL act as "black boxes," making them harder for educators to interpret. Scalability also varies. Hybrid CF and modular architectures efficiently handle large learner populations, whereas deep models and DRL demand significant computation and careful architecture design.

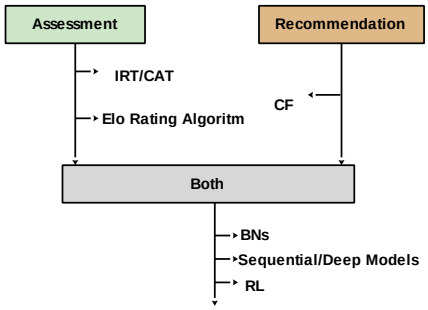


Figure. 1. AL algorithms' core focus

RESEARCH METHOD

The methodology investigates four adaptive learning models within personalized educational systems: collaborative filtering (CF) (Pal et al., 2025; Tong et al., 2025; Obeng et al., 2024), reinforcement learning (RL) (Mon et al., 2023; Yang et al., 2024), Bayesian networks (BNs) (Desmarais et al., 2005; Dai et al., 2023; Zheng, 2025), and Item Response Theory (IRT) (Park et al., 2023). These models were selected for their strong theoretical foundations, established use in adaptive educational technologies, and proven effectiveness in prior research (Adewale et al., 2022; Alshmrany, 2022; Amin et al., 2023; Bock et al., 2021; Chen et al., 2023; Chornous et al., 2021; Choi et al., 2020). Implementation was carried out on a system running Ubuntu 24.04 LTS (64-bit) with Mesa Intel UHD Graphics 620. Data analysis and model development were performed in Python using the Anaconda environment, with gym and rllib for RL, pgmpy for BNs, scikit-surprise for CF, and py-irt for IRT. The hardware setup included a 1 TB hard drive, a 240 GB SSD, 16 GB RAM, and an Intel Core i7-8265U CPU at 2.9 GHz, providing adequate resources for training, simulation, and evaluation.

The empirical evaluation employed the EdNet dataset (Choi et al., 2020; Chen et al., 2023), a large-scale public dataset compiled by the Korean EdTech company Santa in partnership with KAIST. EdNet contains over 131 million interactions from more than 780,000 students, including detailed logs of responses, question attempts, skill tags, feedback, and time spent enabling a realistic simulation of learner behavior. The study adopted a mixed-methods design, combining literature-based conceptual analysis with empirical simulation to examine how each model enhances personalized learning. Models were evaluated on personalization accuracy, adaptability to knowledge changes, responsiveness to feedback, and scalability. Metrics included RMSE for IRT and CF, reward maximization for RL, and posterior probability accuracy for BNs. To address class imbalance within EdNet, the Synthetic Minority Oversampling Technique (SMOTE) was applied, and performance was further evaluated using accuracy, precision, recall, and F1-score. This design ensured alignment with literature-based observations on assessment focus, real-time updating, data requirements, interpretability, and scalability (Adewale et al., 2022; Amin et al., 2023; Bock et al., 2021; Chen et al., 2023; Desmarais et al., 2005; Park et al., 2023; Tong et al., 2025). The models considered and their respective mathematical formulas are as follows:

1) CF predicts a learner's response or rating based on the behaviour of similar learners. A common formula is the weighted sum of neighbour ratings:

$$\hat{r}_{u,i} = \frac{\sum_{v \in N\ (u)} s(u,v).r_{v,i}}{\sum_{v \in N\ (u)} |s(u,v)|} \ldots (1)$$

where, $\hat{r}_{u,i}$ is the predicted rating of learner u for item i, N(u) is the set of similar learners, s(u,v) is the similarity between learners u and v, and $r_{v,i}$ is the rating of learner v for item i (Pal et al., 2025; Tong et al., 2025; Obeng et al., 2024).

2) RL models the learning process as an agent interacting with an environment, updating action values using the Q-learning rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma a' \max Q(s',a') - Q(s,a)] \ldots (2)$$

Where Q(s, a) is the expected reward for taking action aa in state ss, α is the learning rate, γ is the discount factor, r is the reward, and s′ is the next state (Mon et al., 2023; Yang et al., 2024; Pal et al., 2025).

3) BNs model probabilistic relationships between learner variables. The probability of each node given by its parents is:

$$P(X_i \mid Parents(X_i)) \ldots (3)$$

where X_i is a variable representing a learner attribute, and Parents (X_i) are the nodes that directly influence X_i (Desmarais et al., 2005).

4) IRT models the probability of a correct response as a function of learner ability and item characteristics. The two-parameter logistic (2PL) model is:

$$P(\text{correct}) = \frac{1}{1 + e^{-a(\theta - b)}} \dots (4)$$

where θ represents learner ability, a is the item discrimination parameter, and b is the item difficulty parameter (Park et al., 2023).

RESULTS AND DISCUSSION

Model Ranking/Scoring

This sub-section presents the comparative evaluation of four widely used adaptive learning models: IRT, BN, CF, and RL. The models were assessed across six performance features: personalisation accuracy (PA), real-time adaptivity (RTA), cognitive modelling (CM), data requirement (DR), learning outcome prediction (LOP), and explainability (Exp), using a 5-point ordinal scale (1 = Very Low, 5 = Very High). Scores were compiled from studies conducted between 2020 and 2024 (Choi et al., 2020; Chen et al., 2023; Wang et al., 2025) and were based on the analysis in Table 1, which systematically evaluates each model's educational and computational implications.

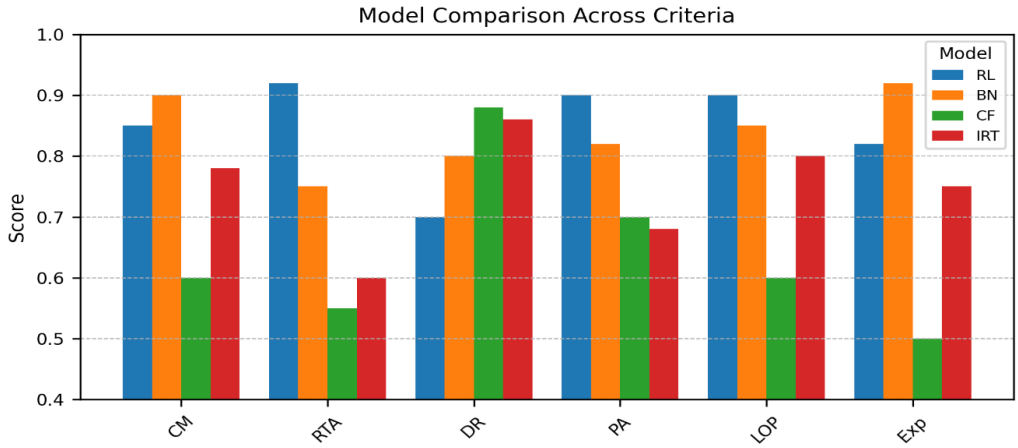


Figure 2. Visualisation of algorithm performance across key features, highlighting RL's dominance in dynamic learning, BN's cognitive strengths, IRT's structured assessment reliability, and CF's data-dependent performance (Choi et al., 2020; Chen et al., 2023; Wang et al., 2025; Liu et al., 2025; Tong et al., 2025).



Figure 3. Model performance across features

As shown in Fig. 2, RL demonstrates the strongest overall performance, leading in real-time adaptivity, personalisation accuracy, and learning outcome prediction, though it requires the most data. BN excels in cognitive modelling and explainability through probabilistic inference. IRT provides moderate performance across features, offering a reliable, structured assessment with low data demands. CF performs adequately in data-rich contexts but is limited in adaptivity and cognitive modelling.

Empirical Results

The EdNet-KT1 dataset subset was used to evaluate four AL models across six metrics. The dataset has the following attributes: 2000 rows and 21 columns, with no missing values; all attributes are continuous numerical values (float 64), and the target is binary (0,1). A scale of (0, 1) was also set to evaluate each of these models, and the results are displayed in Fig. 3. The results show that RL led in real-time adaptivity (92%), personalization (90%), and learning outcome prediction (90%), while BN excelled in cognitive modelling 90% and explainability (92%). IRT and CF performed moderately, limited by psychometric assumptions or reliance on user similarity. Data requirements were highest for RL 70% and CF (88%) and lowest for IRT 86% and BN (80%).

To further improve the performance of the models, we optimized models by improving the quality of the dataset via eliminating class imbalance and evaluated them using the standard ML performance metrics. To achieve this, the models were evaluated with SMOTE balancing and an 80/20 train/test split. Table 6 summarizes the results, while Fig. 4 visualizes the results. As shown in Fig. 4, the comparative results demonstrate that RL achieves the strongest overall performance among the evaluated models. With accuracy reaching 0.9200 in the baseline and 0.9450 with SMOTE, RL consistently leads across precision, recall, and F1-scores for both classes. Notably, its Class 1 recall improves from 93% to 87% with SMOTE, balancing predictive sensitivity without sacrificing accuracy. BN and CF also perform competitively, with accuracy above 91% in baseline models and further gains under SMOTE. Their precision and recall remain balanced across classes, indicating stability in prediction. IRT, while interpretable, shows weaker performance, especially for the minority class, though SMOTE enhances its recall from 62% to 82% and F1-score from 68% to 73%, suggesting improvements are possible when class imbalance is addressed.

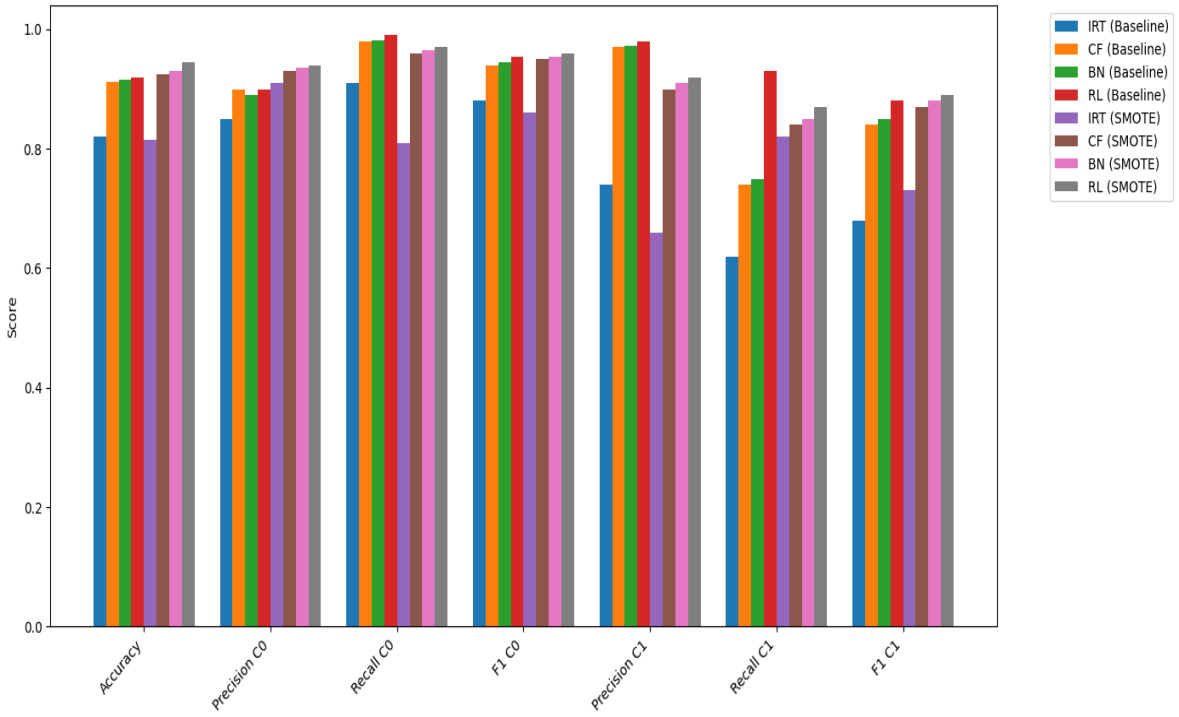


Figure 4. Model performance: Baseline vs SMOTE

From an application perspective, these findings suggest RL is the most effective for adaptive educational systems requiring dynamic sequencing and personalized interventions. Its high performance across all metrics highlights its potential for large-scale, real-time adaptivity. CF and BN emerge as strong alternatives, offering reliable accuracy and balanced class performance, making them suitable for learner modelling and recommendation in e-learning platforms. IRT, despite lower predictive strength, remains valuable in context, prioritizing transparency and psychometric validity. The enhancements observed through SMOTE underscore the importance of handling class imbalance, as it significantly improves minority class prediction and promotes fairness in ALSs. Thus, RL and BN were the most suitable for dynamic and interactive learning, suggesting a hybrid RL–BN approach could optimize adaptive game-based learning.

CONCLUSION

This study conducted a comparative evaluation of four adaptive learning models, IRT, BN, CF, and RL, through literature review, empirical analysis, and experimental validation using the EdNet dataset. The findings show that RL consistently outperformed the other models in personalization accuracy, real-time adaptivity, and long-term outcome prediction, with notable gains in recall and F1-scores for minority learners after SMOTE balancing and hyperparameter tuning. BN followed closely, excelling in cognitive modelling, predictive accuracy, and interpretability, and demonstrating robust improvements under balanced conditions. CF performed moderately, benefiting from data balancing but limited by its dependence on similarity-based inference in dynamic contexts. IRT ranked lowest, retaining value in structured, assessment-driven applications due to its efficiency and explainability, but showing minimal adaptability across scenarios. Overall, RL and BN emerge as the most effective models for modern ADLs. Their complementary strengths, RL's dynamic personalization and BN's cognitive transparency, highlight the potential of a hybrid RL-BN approach to combine responsiveness with interpretability. Such integration offers a pathway to building AL environments that are not only effective and scalable but also equitable and pedagogically grounded, advancing the promise of personalized education for diverse learners. As part of our future works, RL and BN will be applied to design dynamic and interactive learning, specifically, adaptive game-based learning and intelligent tutoring systems to enhance programming experience.

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REFERENCES

Adewale, O. S., Agbonifo, O. C., Ibam, E. O., Makinde, A. I., Boyinbode, O. K., Ojokoh, B. A., & Olatunji, S. O. (2022). Design of a personalised adaptive ubiquitous learning system. *Interactive Learning Environments, 32*(1), 208–228. https://doi.org/10.1080/10494820.2022.2084114

Alshmrany, S. (2022). Adaptive learning style prediction in e-learning environment using Levy flight distribution based CNN model. *Cluster Computing, 25*, 523–536. https://doi.org/10.1007/s10586-021-03403-3

Amin, S., Uddin, M. I., Alarood, A. A., Mashwani, W. K., Alzahrani, A., & Alzahrani, A. O. (2023). Smart e-learning framework for personalised adaptive learning and sequential path recommendations using reinforcement learning. *IEEE Access, 11*, 89769–89790. https://doi.org/10.1109/ACCESS.2023.3305584

Bock, R. D., & Gibbons, R. D. (2021). Computerised adaptive testing. In R. D. Bock & R. D. Gibbons (Eds.), *Item response theory*. https://doi.org/10.1002/9781119716723.ch8

Chen, F., Lu, C., Cui, Y., & Gao, Y. (2023). Learning outcome modelling in computer-based assessments for learning: A sequential deep collaborative filtering approach. *IEEE*

Transactions on Learning Technologies, 16(2), 243–255. https://doi.org/10.1109/TLT.2022.3224075

Choi, Y., Lee, Y., Shin, D., Cho, J., Park, S., Lee, S., Baek, J., Bae, C., Kim, B., & Heo, J. (2020). EdNet: A large-scale hierarchical dataset in education. In *Proceedings of AIED 2020*, 69–73. Springer.

Chornous, G., Nikolskyi, I., Wyszyński, M., Kharlamova, G., & Stolarczyk, P. (2021). A hybrid user-item-based collaborative filtering model for e-commerce recommendations. *Journal of International Studies, 14*, 157–173. https://doi.org/10.14254/2071-8330.2021/14-4/11

Dai, J., Gu, X., & Zhu, J. (2023). Personalised recommendation in the adaptive learning system: The role of adaptive testing technology. *Journal of Educational Computing Research, 61*(3), 523–545. https://doi.org/10.1177/07356331221127303

Desmarais, M. C., & Pu, X. (2005). A Bayesian student model without hidden nodes and its comparison with item response theory. *International Journal of Artificial Intelligence in Education, 15*(4), 291–323. https://doi.org/10.3233/IRG-2005-15(4)03

Dey, A., Ganguly, A., Banik, I. R., Bhuiya, S., Sengupta, S., & Das, R. (2025). Smart recommendation system in e-learning using machine learning and data analytics. *SN Computer Science, 6*, 706. https://doi.org/10.1007/s42979-025-04249-x

El Maazouzi, Q., Retbi, A., & Bennani, S. (2024). Enhancing online learning: Sentiment analysis and collaborative filtering from Twitter social network for personalised recommendations. *International Journal of Electrical and Computer Engineering, 14*(3), http://doi.org/10.11591/ijece.v14i3.pp3266-3276

Elegbeleye, F. A., & Bassey, I. (2025). A systematic review of challenges in teaching and learning computer programming modules. *The Indonesian Journal of Computer Science, 14*(1). https://doi.org/10.33022/ijcs.v14i1.4592

Elegbeleye, F., Mbodila, M., Mabovana, A., & Esan, O. (2022). Data privacy on using four models: A review. In *Proceedings of the International Conference on Electrical, Computer and Energy Technologies (ICECET 2022)*, 1–9. IEEE. https://doi.org/10.1109/ICECET55527.2022.9872999

Essa, S. G., Celik, T., & Human-Hendricks, N. E. (2023). Personalised adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review. *IEEE Access, 11*, 48392–48409. https://doi.org/10.1109/ACCESS.2023.3276439

Essa, S. G., Celik, T., & Human-Hendricks, N. E. (2023). Personalised adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review. *IEEE Access, 11*, 48392–48409. https://doi.org/10.1109/ACCESS.2023.3276439

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. *Education Sciences, 13*(12), 1216. https://doi.org/10.3390/educsci13121216

Khababa, G., Bessou, S., Seghir, F., Harun, N. H., Almazyad, A. S., & Jangir, P. (2025). Collaborative filtering techniques for predicting web service QoS values in static and dynamic environments: A systematic and thorough analysis. *IEEE Access, 13*, 45350–45376. https://doi.org/10.1109/ACCESS.2025.3550284

Li, Q. (2024). Adaptive recommendation of teaching content in higher education using mobile interaction technology. *International Journal of Interactive Mobile Technologies, 18*(24), 115–129. https://doi.org/10.3991/ijim.v18i24.53091

Liu, H., Xiong, X., Li, P., Zhao, P., & Wu, X. (2025). Dynamic graph learning to denoise implicit feedback for graph collaborative filtering. *IEEE Transactions on Computational Social Systems*. https://doi.org/10.1109/TCSS.2025.3564762

Liu, R. (2024). Simulation of e-learning in English personalised learning recommendation system based on Markov chain algorithm and adaptive learning algorithm. *Entertainment Computing, 51*, 100719. https://doi.org/10.1016/j.entcom.2024.100719

Luo, G., Gu, H., Dong, X., et al. (2025). HA-LPR: A highly adaptive learning path recommendation. *Education and Information Technologies, 30*, 14597–14627. https://doi.org/10.1007/s10639-025-13395-x

Ma, Y., Wang, L., Zhang, J., Liu, F., & Jiang, Q. (2023). A personalised learning path recommendation method incorporating multi-algorithm. *Applied Sciences, 13*(10), 5946. https://doi.org/10.3390/app13105946

Mejeh, M., & Rehm, M. (2024). Taking adaptive learning in educational settings to the next level: Leveraging natural language processing for improved personalisation. *Educational Technology Research and Development, 72*, 1597–1621. https://doi.org/10.1007/s11423-024-10345-1

Mon, B. F., Wasfi, A., Hayajneh, M., Slim, A., & Abu Ali, N. (2023). Reinforcement learning in education: A literature review. *Informatics, 10*(3), 74. https://doi.org/10.3390/informatics10030074

Obeng, A. Y., Opoku, S. K., Kotei, E., & Obeng, A. P. (2024). Effects of information technology modularity on content-boosted collaborative filtering e-learning recommenders. *Cognisance Journal of Multidisciplinary Studies, 4*(12), 228–243. https://doi.org/10.47760/cognisance.2024.v04i12.023

Pal, S., Pramanik, P. K. D., & Choudhury, P. (2025). Learner's intention analysis to mitigate the cold start problem in personalised learning recommendation systems. *Multimedia Tools and Applications, 84*, 21273–21327. https://doi.org/10.1007/s11042-024-19806-4

Park, J. Y., Dedja, K., Pliakos, K., Kim, J., Joo, S., Cornillie, F., Vens, C., & den Noortgate, W. V. (2023). Comparing the prediction performance of item response theory and machine learning methods on item responses for educational assessments. *Behavior Research Methods, 55*(4), 2109–2124. https://doi.org/10.3758/s13428-022-01910-8

Pelánek, R. (2024). Leveraging response times in learning environments: Opportunities and challenges. *User Modeling and User-Adapted Interaction, 34*(3), 729–752. https://doi.org/10.1007/s11257-023-09386-7

Safarov, F., Kutlimuratov, A., Abdusalomov, A. B., Nasimov, R., & Cho, Y.-I. (2023). Deep learning recommendations of e-education based on clustering and sequence. *Electronics, 12*(4), 809. https://doi.org/10.3390/electronics12040809

Staufer, et al. (2025). *A tool landscape for adaptive learning* (pp. 30–39). https://doi.org/10.1145/3723010.3723028

Tong, C., & Ren, C. (2025). Deep knowledge tracing and cognitive load estimation for personalised learning path generation using neural network architecture. *Scientific Reports, 15*, 24925. https://doi.org/10.1038/s41598-025-10497-x

Wang, S., Qiu, L., & Sun, C. (2025). Adaptive education system for drama education in college education system based on human–computer interaction. *International Journal of Human–Computer Interaction, 41*(3), 1872–1887. https://doi.org/10.1080/10447318.2022.2079169

Wei, Q., & Yao, X. (2022). Personalised recommendation of learning resources based on knowledge graph. In *Proceedings of the 11th International Conference on Educational and Information Technology (ICEIT 2022)* (pp. 46–50). https://doi.org/10.1109/ICEIT54416.2022.9690758

Yang, G., Xie, G., Wang, J., et al. (2024). Adaptive task recommendation based on reinforcement learning in mobile crowd sensing. *Applied Intelligence, 54*, 2277–2299. https://doi.org/10.1007/s10489-023-05247-3

Yuan, S. (2025). Research on the design of an adaptive learning system based on artificial intelligence-driven learning. In *Proceedings of the 2nd International Conference on Informatics Education and Computer Technology Applications (IECA'25)* (pp. 46–52). Association for Computing Machinery. https://doi.org/10.1145/3732801.3732811

Zheng, C. (2025). Application of Bayesian networks in adaptive listening assessment system in a flipped English learning environment. *Journal of Computational Methods in Sciences and Engineering, 25*(4), 3197–3209. https://doi.org/10.1177/14727978251318809

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