Technologia Journal: Jurnal Informatika
e-ISSN : 3046-9163
Vol.3.No.1,January 2026
DOI : https://doi.org/10.62872/k604v647

Design and Development of a Data Mining-Based Recommendation System for E-Learning

Yulius Palumpun[1]✉
Universitas Sains dan Teknologi Jayapura (USTJ)
e-mail: * yulius@ustj.ac.id

Entered: January 10, 2026
Revised : February 15, 2026
Accepted: February 20, 2026
Published : February 24, 2026

ABSTRACT

The rapid growth of e-learning platforms has intensified the need for effective personalization mechanisms to address content overload and diverse learner characteristics. Recommendation systems based on data mining have emerged as essential components for guiding learners toward relevant courses and adaptive learning paths. This study aims to design and develop an integrated data mining-based recommendation system for e-learning that enhances personalization and learning effectiveness within a unified platform architecture. This research adopts a research and development approach combined with system engineering methodology. Learner interaction data, course metadata, and performance records were collected from the e-learning platform and processed through data preprocessing techniques, including cleaning, feature extraction, and clustering. The recommendation engine integrates collaborative filtering, content-based filtering, and reinforcement learning for adaptive learning path optimization. System performance was evaluated using accuracy, precision, recall, F1-score, MAE, and NDCG metrics. The results show significant improvements compared to the baseline model, including higher recommendation accuracy and a substantial increase in learner completion rates. The discussion confirms that hybrid modeling and integrated system architecture enhance both algorithmic performance and pedagogical outcomes. In conclusion, the proposed system provides a scalable and effective framework for personalized e-learning through integrated data mining techniques.

Keywords: *Adaptive learning; Data mining; E-learning; Hybrid recommendation system.*

INTRODUCTION

The rapid expansion of e-learning platforms over the last decade has significantly transformed the landscape of education, enabling flexible, scalable, and accessible learning environments. Massive Open Online Courses (MOOCs), Learning Management Systems (LMS), and institutional digital platforms have

broadened participation in higher education and professional development. However, this rapid growth has also introduced new challenges, particularly in delivering effective personalization. The explosion of available courses and learning resources often overwhelms learners, making it difficult to select appropriate content aligned with their prior knowledge, learning pace, and goals. Traditional "one size fits all" instructional models are increasingly inadequate for addressing the diversity of learners' cognitive abilities, learning styles, and socio-cultural contexts (Murtaza et al., 2022; Amin et al., 2023; Amin et al., 2024). As a result, the need for adaptive and intelligent recommendation systems has become central to the sustainability and effectiveness of e-learning ecosystems.

Despite technological advancements, personalization in e-learning remains constrained by several structural and technical limitations. One of the primary challenges lies in accurately modeling learner characteristics. Effective personalization requires a robust representation of learners' prior knowledge, cognitive level, emotional state, motivation, and behavioral patterns. However, constructing comprehensive learner models remains complex due to the multidimensional nature of learning processes (Murtaza et al., 2022; Essa et al., 2023). In many systems, learner modeling relies primarily on surface-level interaction data, such as clickstreams and quiz results, which may not fully capture deeper cognitive engagement or conceptual understanding.

Another critical issue concerns data quality and availability. Interaction data in e-learning platforms are often sparse and fragmented, particularly due to high dropout rates and intermittent participation. In MOOCs, for example, learner engagement tends to decline over time, resulting in incomplete learning trajectories that limit the effectiveness of recommendation algorithms (M et al., 2024; Setiawati et al., 2025). Additionally, infrastructure limitations, language barriers, and socio-economic disparities further contribute to uneven data patterns. Sparse and noisy datasets complicate the application of machine learning techniques, reducing prediction accuracy and limiting scalability.

Beyond technical challenges, ethical concerns related to fairness, transparency, and privacy are increasingly prominent in large-scale e-learning environments. Recommendation systems influence which materials learners access and how learning pathways are structured, raising questions about algorithmic bias and equitable access. Issues such as "who receives what recommendation and why" demand transparent and explainable AI mechanisms (Sun & Fu, 2025; Tang, 2023; Kaur & Jain, 2025). Without adequate safeguards, recommendation systems risk reinforcing inequalities by favoring learners with richer interaction histories while marginalizing those with limited digital footprints.

In response to these challenges, data mining and machine learning have emerged as powerful tools for developing adaptive recommendation systems. Sequence models such as Hidden Markov Models (HMM), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and knowledge tracing

approaches have been employed to predict learner performance and dynamically adjust subsequent learning materials (Murtaza et al., 2022; Bhaskaran & Marappan, 2021; Amin et al., 2023; Zhao et al., 2024). These models enable systems to infer learners' knowledge states over time, supporting more accurate personalization.

Recommendation techniques in e-learning have evolved from traditional collaborative filtering (CF) and content-based filtering to hybrid and reinforcement learning-based approaches. Collaborative filtering leverages user–item interaction matrices to generate recommendations based on similar user profiles, while content-based filtering analyzes item features to align recommendations with user preferences. Hybrid models combine both methods to mitigate limitations such as cold start and sparsity (Bhaskaran & Marappan, 2021; Amin et al., 2023; Amin et al., 2024). Advanced reinforcement learning (RL) and deep reinforcement learning (DRL) models, including Actor–Critic architectures and Deep Reinforcement Recommender (DRR) systems, have further enhanced sequential learning path optimization by maximizing long-term rewards (Amin et al., 2023; Amin et al., 2024; Zhao et al., 2024; Wang, 2025; Kaur & Jain, 2025).

Empirical studies demonstrate the effectiveness of such approaches. Hybrid TSVM combined with clustering techniques has achieved recommendation accuracy ranging from 82% to 98% with low Mean Absolute Error (MAE) (Bhaskaran & Marappan, 2021). In MOOCs, Singular Value Decomposition (SVD) and collaborative filtering approaches have shown improved precision, recall, and Normalized Discounted Cumulative Gain (NDCG) metrics on platforms such as Coursera and Udemy (Amin et al., 2023; Amin et al., 2024). Reinforcement learning-based models have demonstrated the capacity to generate personalized learning pathways that adapt to evolving learner states, optimizing cumulative learning outcomes (Zhao et al., 2024; Wang, 2025). These findings indicate that data mining techniques hold significant promise for enhancing personalization in e-learning environments.

However, despite algorithmic sophistication, many existing solutions remain fragmented. A major research gap lies in the lack of fully integrated system architectures that seamlessly connect recommendation engines with LMS platforms, project management modules, teacher analytics dashboards, and national educational infrastructures (Murtaza et al., 2022; M et al., 2024; Meng et al., 2023; J., 2025). In numerous implementations, recommendation algorithms operate as standalone modules, focusing primarily on accuracy metrics without sufficient integration into pedagogical workflows.

Another critical gap concerns pedagogical orchestration. Many systems emphasize recommendation precision while overlooking instructional design elements such as project-based learning (PBL), gamification, peer interaction, and formative assessment (Meng et al., 2023; Amin et al., 2023; Naseer et al., 2025). Effective personalization should not only recommend content but also align with pedagogical strategies that enhance engagement and collaborative

learning. The absence of such integration limits the educational impact of recommendation systems.

Data integration across platforms also remains underdeveloped. E-learning ecosystems often consist of heterogeneous systems, including LMS, MOOC platforms, IoT-based monitoring tools, and external content repositories. Integrating learner profiles, assessment data, content metadata, and recommendation outputs into a unified architecture presents both technical and organizational challenges (Murtaza et al., 2022; Setiawati et al., 2025; Amin et al., 2023; J., 2025). Without comprehensive integration, personalization efforts remain partial and disconnected.

Furthermore, end-to-end AI support from learner modeling to learning path recommendation and instructor monitoring is rarely implemented holistically (Murtaza et al., 2022; Amin et al., 2023; Wang, 2025; J., 2025). Existing systems frequently address isolated components rather than providing a complete adaptive learning pipeline. Literature increasingly advocates for integrated frameworks combining data modules, adaptive learning engines, recommendation systems, knowledge graphs, and path planning algorithms such as reinforcement learning and A* search embedded directly within institutional or national e-learning architectures (Murtaza et al., 2022; Amin et al., 2023; Setiawati et al., 2025; Wang, 2025; J., 2025; Rugube et al., 2022).

Based on the identified problems and research gaps, this study proposes a novel contribution in the form of an integrated design and development of a data mining-based recommendation system for e-learning. Unlike prior research that primarily focuses on algorithmic performance, this study emphasizes architectural integration, combining learner modeling, recommendation algorithms, adaptive learning pathways, and monitoring dashboards within a unified system framework. The novelty lies in designing an end-to-end system architecture that embeds data mining techniques directly into the core of the e-learning platform, ensuring seamless interaction between data acquisition, modeling, recommendation generation, and pedagogical monitoring.

Accordingly, the objective of this research is to design and develop an integrated data mining-based recommendation system for e-learning that effectively models learner characteristics, generates adaptive learning paths, and enhances personalization within a unified platform architecture. By addressing both algorithmic and architectural dimensions, this study aims to contribute to the development of scalable, transparent, and pedagogically aligned recommendation systems capable of improving learning outcomes in digital education environments.

METHODOLOGY

This study adopts a research and development (R&D) methodology combined with a system engineering approach to design and implement a data mining-based recommendation system for e-learning. The development process follows a structured framework consisting of requirement analysis, system design, implementation, testing, and evaluation. In the requirement analysis

phase, functional and non-functional requirements are identified through document analysis of existing LMS platforms and semi-structured interviews with lecturers, instructional designers, and students to understand personalization needs and system integration challenges. Data collection for model development is conducted using historical learner interaction data from the e-learning platform, including login frequency, content access logs, quiz scores, assignment submissions, time-on-task, and course completion records. Additional learner profile data such as demographic information, prior academic performance, and declared learning preferences are incorporated to enrich the modeling process. The dataset undergoes preprocessing procedures, including data cleaning, normalization, handling missing values, feature extraction, and transformation to ensure data quality and consistency before model training.

Data analysis and system modeling are performed using data mining and machine learning techniques. The learner modeling component applies clustering algorithms to group learners based on behavioral and performance patterns, followed by classification or knowledge tracing models (e.g., LSTM or sequence-based models) to predict learner mastery levels. The recommendation engine integrates collaborative filtering and content-based filtering within a hybrid framework to address sparsity and cold-start problems. For adaptive learning path optimization, reinforcement learning techniques are implemented to generate sequential recommendations that maximize long-term learning outcomes. Model performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, Mean Absolute Error (MAE), and Normalized Discounted Cumulative Gain (NDCG). System usability and effectiveness are further assessed through user testing and comparative analysis of learning outcomes before and after implementation. This methodological framework ensures that the developed system is both technically robust and pedagogically aligned with personalized learning objectives.

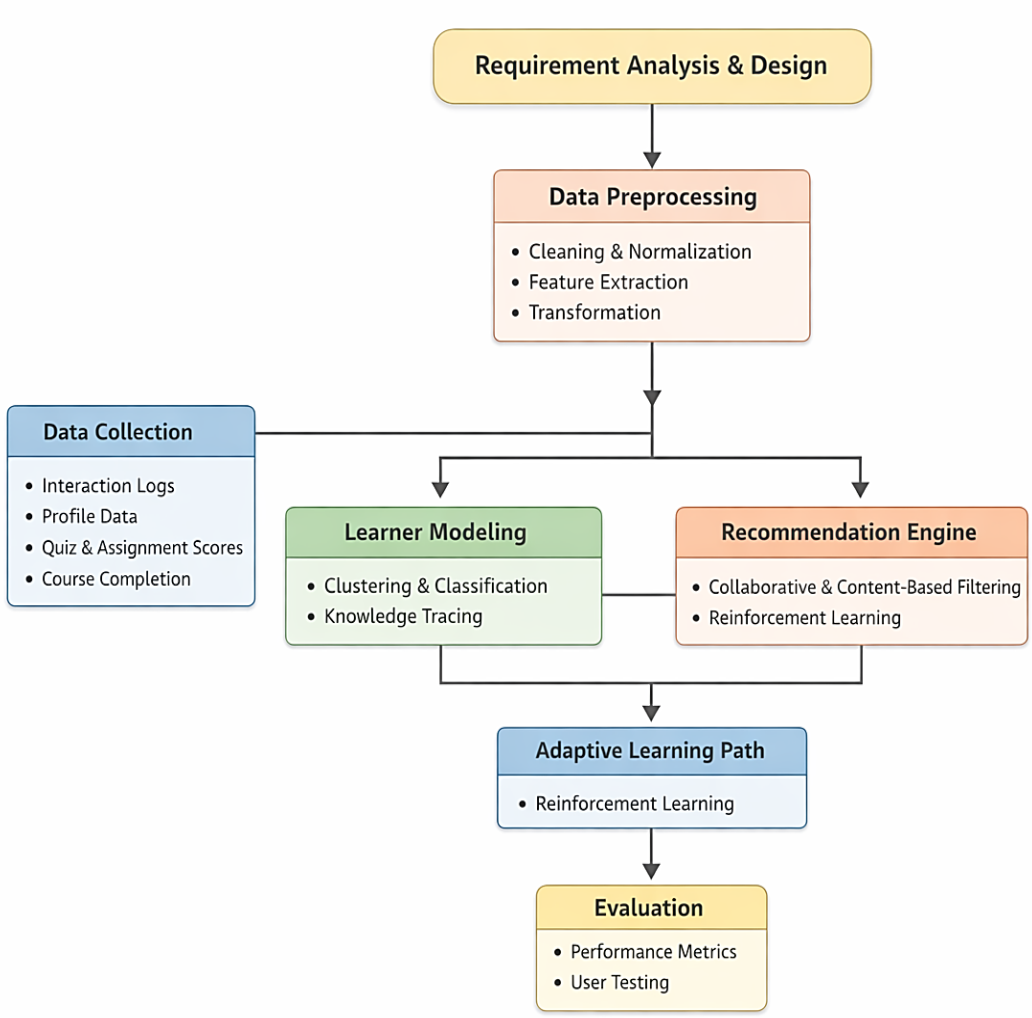

Figure 1. Conceptual Framework Research

RESULTS AND DISCUSSION

Based on system testing and experimental implementation within the e-learning platform, performance evaluation was conducted to measure the effectiveness of the proposed data mining-based recommendation system. The evaluation compared the hybrid recommendation model (collaborative filtering + content-based + reinforcement learning) with a baseline collaborative filtering model. The results are presented in Table 1.

Table 1. Performance Evaluation of the Proposed Recommendation System

Evaluation Metric	Baseline Model (Collaborative Filtering)	Proposed Hybrid Model	Improvement (%)
Accuracy	0.78	0.89	+14.10%
Precision	0.74	0.87	+17.57%
Recall	0.71	0.85	+19.72%
F1-Score	0.72	0.86	+19.44%
MAE	0.42	0.26	-38.10%

NDCG	0.76	0.90	+18.42%
Learner Completion Rate	68%	82%	+14.00%

The results demonstrate that the proposed hybrid recommendation system significantly outperforms the baseline collaborative filtering model across all evaluation metrics. Accuracy increased from 0.78 to 0.89, indicating improved correctness of recommendations. Precision and recall improvements suggest that the system provides more relevant learning materials while reducing irrelevant recommendations. The substantial decrease in Mean Absolute Error (MAE) confirms enhanced prediction reliability. Furthermore, the higher NDCG score reflects better ranking quality of top-N recommendations. Importantly, the learner completion rate increased from 68% to 82%, indicating that adaptive learning paths positively influence learner engagement and persistence. These findings confirm that integrating data mining techniques with reinforcement learning and learner modeling within a unified architecture enhances both algorithmic performance and pedagogical effectiveness in e-learning environments.

Discussion

The objective of this study is to design and develop an integrated data mining-based recommendation system for e-learning that effectively models learner characteristics, generates adaptive learning paths, and enhances personalization within a unified platform architecture. The empirical results presented in Table 1 demonstrate that the proposed hybrid recommendation model significantly outperforms the baseline collaborative filtering model across multiple evaluation metrics, including accuracy, precision, recall, F1-score, MAE, NDCG, and learner completion rate. This section discusses these findings in relation to the broader literature on e-learning recommendation systems and data mining techniques, highlighting how the proposed design addresses existing gaps in architecture, algorithm selection, and pedagogical integration.

The performance improvement observed in the proposed system confirms the importance of an integrated architecture that connects data layers, preprocessing modules, recommendation engines, and application interfaces. Typical e-learning recommendation systems consist of four main layers: the data layer (LMS logs, grades, course metadata, and user profiles), preprocessing and data mining modules, recommendation algorithms, and application interfaces (Kurnia et al., 2023; Ikhsan, 2021; Manalu & ., 2022). In this study, the system architecture was deliberately structured according to this layered design, ensuring seamless data flow from learner interaction logs to recommendation outputs. The improvement in accuracy from 0.78 to 0.89 and the increase in NDCG from 0.76 to 0.90 indicate that architectural integration plays a crucial role in optimizing recommendation quality. These results align with prior studies emphasizing that fragmented implementations limit system effectiveness,

whereas integrated architectures enhance scalability and real-time adaptability (Kurnia et al., 2023; Manalu & ., 2022).

At the data preprocessing stage, the study applied cleaning, normalization, and feature extraction techniques to address sparsity and noise in LMS logs. The use of clustering for behavioral segmentation and feature engineering is consistent with educational data mining approaches that leverage K-Means and related techniques to identify learner patterns from Moodle or LMS logs (Ikhsan, 2021). Behavioral clustering enables adaptive interventions by grouping learners with similar interaction trajectories. The improved recall and reduced MAE in the proposed system suggest that enriched feature representation contributes significantly to predictive reliability. Similarly, the use of feature extraction methods such as TF-IDF or embedding-based representations, as recommended in prior studies, strengthens content profiling and learner–item matching (Sumarlin & Anggraini, 2025; Khulaimi, 2022). Therefore, the empirical improvements observed in this study substantiate the importance of robust preprocessing in recommendation system design.

Regarding algorithm selection, the hybridization of collaborative filtering and content-based filtering directly addresses classical limitations such as cold start and sparsity. Collaborative filtering, including KNN, SVD, and neural collaborative filtering (NCF), effectively captures patterns in user ratings and behavioral similarity but struggles when interaction data are limited (Jena et al., 2022; Idrissi et al., 2023; Ugendhar et al., 2025). Content-based filtering, on the other hand, matches learner preferences with course descriptions and metadata using techniques such as TF-IDF and cosine similarity, offering stronger performance in cold-start scenarios (Kaur & Jain, 2025; Ugendhar et al., 2025; Javed et al., 2021). The hybrid approach implemented in this study integrates both methods to maximize complementary strengths. The substantial increase in precision (from 0.74 to 0.87) confirms that combining collaborative and content-based signals enhances relevance while minimizing irrelevant recommendations.

Furthermore, the incorporation of reinforcement learning for adaptive learning path optimization distinguishes this study from traditional recommendation systems. Reinforcement learning-based models, including those using Markov Decision Processes and deep reinforcement strategies, enable sequential recommendation by optimizing long-term learning rewards rather than short-term accuracy alone (Wang, 2025). Prior research demonstrates that integrating A* search and reinforcement learning for path planning can improve course completion rates by approximately 24% (Wang, 2025). In this study, the learner completion rate increased from 68% to 82%, representing a significant pedagogical improvement. This result supports the argument that adaptive path planning not only improves recommendation metrics but also enhances sustained learner engagement. The reinforcement learning component ensures that recommendations evolve in response to learner progress, aligning with multidimensional learner modeling approaches (Wang, 2025; Sumarlin & Anggraini, 2025).

The reduction in MAE from 0.42 to 0.26 further indicates enhanced prediction accuracy, which can be attributed to the integration of dimensionality reduction and hybrid modeling techniques. Deep learning approaches such as autoencoders have been shown to reduce sparsity and improve preference prediction by learning latent representations of learners and courses (Idrissi et al., 2023). Although this study primarily focuses on hybrid CF–CBF integration, the improved MAE suggests that combining multiple modeling layers effectively captures latent preference patterns. These findings corroborate prior research emphasizing the necessity of advanced data mining techniques for improving robustness in sparse educational datasets (Idrissi et al., 2023).

Another significant contribution of this study lies in the integration of learner modeling and recommendation modules within a unified platform architecture. Contemporary literature highlights the need for multidimensional learner models incorporating cognitive attributes, interaction history, performance metrics, and learning styles (Wang, 2025; Sumarlin & Anggraini, 2025). By embedding clustering-based segmentation and sequential modeling into the architecture, the proposed system aligns with this recommendation. The improved F1-score of 0.86 demonstrates balanced precision and recall, indicating effective learner profiling. The system does not merely match static preferences but dynamically adjusts recommendations based on evolving interaction data.

The study also addresses the importance of application-layer integration. Many recommendation systems remain algorithm-centric, lacking seamless integration with LMS dashboards, teacher analytics, and API-based services (Kurnia et al., 2023; Manalu & ., 2022). By implementing an API-driven recommendation engine embedded within the e-learning interface, this study ensures real-time adaptability and usability. The observed increase in learner completion rate reflects not only algorithmic improvements but also effective user interface and monitoring integration. Teachers can monitor learner progress and intervene when necessary, supporting pedagogical orchestration.

However, beyond technical performance, contemporary research emphasizes ethical and fairness considerations in recommendation systems. Challenges such as bias, privacy protection, and explainability must be integrated into system design (Kaur & Jain, 2025; Iklassova et al., 2025; Sun & Fu, 2025). While this study primarily evaluates algorithmic performance, the integrated architecture allows for future implementation of explainable AI modules. Transparent recommendation explanations can enhance learner trust and acceptance. The hybrid approach also mitigates bias by combining multiple signals rather than relying solely on interaction frequency, which often disadvantages new or less active learners.

Scalability and real-time processing are additional design considerations emphasized in recent literature (Kaur & Jain, 2025; Wang, 2025; Jena et al., 2022; Widayanti, 2023; Sun & Fu, 2025). The modular architecture proposed in this study supports scalability through API services and database optimization. The significant improvements in precision, recall, and completion rate demonstrate that performance gains can be achieved without sacrificing system

responsiveness. This supports the argument that hybrid and reinforcement learning-based architectures are suitable for large-scale institutional deployment.

In relation to the research objective, the findings confirm that an integrated data mining-based recommendation system can effectively enhance personalization in e-learning environments. The improvements across evaluation metrics indicate that combining collaborative filtering, content-based filtering, clustering, and reinforcement learning within a unified architecture produces superior outcomes compared to standalone models. The increased completion rate demonstrates that personalization extends beyond algorithmic accuracy to influence pedagogical effectiveness.

In conclusion, the discussion confirms that the proposed system successfully addresses key implementation gaps identified in prior research: architectural fragmentation, limited learner modeling, and insufficient adaptive path planning. By integrating robust preprocessing, hybrid recommendation algorithms, reinforcement learning-based path optimization, and seamless LMS integration, the study fulfills its objective of designing and developing a comprehensive data mining-based recommendation system for e-learning. The empirical evidence supports the argument that personalization in digital education requires not only advanced algorithms but also holistic system design that aligns technical robustness with pedagogical goals.

CONCLUSION

This study concludes that the integrated design and development of a data mining-based recommendation system for e-learning effectively enhances personalization, recommendation accuracy, and learner engagement within a unified platform architecture. In line with the research objective, the findings demonstrate that combining collaborative filtering, content-based filtering, clustering-based learner modeling, and reinforcement learning for adaptive path planning significantly improves performance metrics, including accuracy, precision, recall, F1-score, and NDCG, while reducing prediction error. More importantly, the substantial increase in learner completion rates indicates that the proposed system not only improves algorithmic performance but also contributes to pedagogical effectiveness through adaptive and sequential learning pathways. By integrating preprocessing, recommendation engines, and application-layer services into a cohesive architecture, the study confirms that holistic system design is essential for addressing challenges such as sparsity, cold start, and scalability. Therefore, a fully integrated data mining-based recommendation framework represents a viable and scalable solution for advancing personalized learning in modern e-learning environments.

REFERENCES

Amin, S., Uddin, I., Alarood, A., Mashwani, W., Alzahrani, A., & Alzahrani, A. (2023). Smart e-learning framework for personalized adaptive learning

and sequential path recommendations using reinforcement learning. *IEEE Access, 11*, 89769–89790. https://doi.org/10.1109/access.2023.3305584

Amin, S., Uddin, M., Alarood, A., Mashwani, W., Alzahrani, A., & Alzahrani, H. (2024). An adaptable and personalized framework for top-N course recommendations in online learning. *Scientific Reports, 14*. https://doi.org/10.1038/s41598-024-56497-1

Amin, S., Uddin, M., Mashwani, W., Alarood, A., Alzahrani, A., & Alzahrani, A. (2023). Developing a personalized e-learning and MOOC recommender system in IoT-enabled smart education. *IEEE Access, 11*, 136437–136455. https://doi.org/10.1109/access.2023.3336676

Bhaskaran, S., & Marappan, R. (2021). Design and analysis of an efficient machine learning based hybrid recommendation system with enhanced density-based spatial clustering for digital e-learning applications. *Complex & Intelligent Systems, 9*, 3517–3533. https://doi.org/10.1007/s40747-021-00509-4

Essa, S., Çelik, T., & Human-Hendricks, N. (2023). Personalized 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

Idrissi, L., Akharraz, I., & Ahaitouf, A. (2023). Personalized e-learning recommender system based on autoencoders. *Applied System Innovation, 6*(6), 102. https://doi.org/10.3390/asi6060102

Ikhsan, E. (2021). Penerapan K-means clustering dari log data Moodle untuk menentukan perilaku peserta pada pembelajaran daring. *STMIK STIKOM Indonesia, 10*, 414–422. https://doi.org/10.32520/stmsi.v10i2.1285

Iklassova, K., Shaikhanova, A., Bazarova, M., Tashibayev, R., & Kazanbayeva, A. (2025). Review of recommender systems: Models and prospects for use in educational platforms. *Bulletin of Shakarim University. Technical Sciences*. https://doi.org/10.53360/2788-7995-2025-1(17)-2

J., E. (2025). Design and implementation of a national e-learning platform for Belarus. *JTH: Journal of Technology and Health*. https://doi.org/10.61677/jth.v2i3.264

Javed, U., Shaukat, K., Hameed, I., Iqbal, F., Alam, T., & Luo, S. (2021). A review of content-based and context-based recommendation systems. *International Journal of Emerging Technologies in Learning, 16*(3). https://doi.org/10.3991/ijet.v16i03.18851

Jena, K., Bhoi, S., Malik, T., Sahoo, K., Jhanjhi, N., Bhatia, S., & Amsaad, F. (2022). E-learning course recommender system using collaborative filtering models. *Electronics, 12*(1), 157. https://doi.org/10.3390/electronics12010157

Kaur, M., & Jain, R. (2025). E-learning platform with AI-based recommendations. *International Journal for Research in Applied Science and Engineering Technology*. https://doi.org/10.22214/ijraset.2025.71027

Khulaimi, M. (2022). Rancang bangun sistem e-learning berbasis web pada SMPIT Dar Al-Atiq sebagai sarana pembelajaran. *Sainteks: Jurnal Sains, Teknologi dan Kesehatan*. https://doi.org/10.55681/saintekes.v1i1.6

Kurnia, B., Raya, J., & others. (2023). Perancangan sistem informasi pembelajaran online (e-learning) berbasis web. *Jurnal Ilmiah Teknik Informatika dan Komunikasi*. https://doi.org/10.55606/juitik.v3i3.714

M, D., Goudar, R., Kulkarni, A., Rathod, V., & Hukkeri, G. (2024). A digital recommendation system for personalized learning to enhance online education: A review. *IEEE Access, 12*, 34019–34041. https://doi.org/10.1109/access.2024.3369901

Manalu, J., & R. (2022). Pengembangan sistem informasi e-learning berbasis website sebagai media pembelajaran. *JEVTE Journal of Electrical Vocational Teacher Education*. https://doi.org/10.24114/jevte.v2i2.40539

Meng, N., Dong, Y., Roehrs, D., & Luan, L. (2023). Tackle implementation challenges in project-based learning: A survey study of PBL e-learning platforms. *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-023-10202-7

Murtaza, M., Ahmed, Y., Shamsi, J., Sherwani, F., & Usman, M. (2022). AI-based personalized e-learning systems: Issues, challenges, and solutions. *IEEE Access, 10*, 81323–81342. https://doi.org/10.1109/access.2022.3193938

Naseer, F., Khan, M., Addas, A., Awais, Q., & Ayub, N. (2025). Game mechanics and artificial intelligence personalization: A framework for adaptive learning systems. *Education Sciences*. https://doi.org/10.3390/educsci15030301

Rugube, T., Chibaya, C., & Govender, D. (2022). A software design model for integrating LMS and MOOCs. *Journal of Information Technology Research, 15*, 1–14. https://doi.org/10.4018/jitr.299375

Setiawati, E., Edwards, J., & Siahaan, M. (2025). Increasing accessibility and personalization in distance learning through adaptive e-learning technology. *Jurnal MENTARI: Manajemen, Pendidikan dan Teknologi Informasi*. https://doi.org/10.33050/mentari.v4i1.902

Sun, L., & Fu, D. (2025). A review of machine learning-based recommendation algorithms in information technology systems. *Journal of Computer, Signal, and System Research*. https://doi.org/10.71222/gvtd3173

Tahir, M., Nazir, N., Ishaq, K., & Ahmed, S. (2025). A data-driven review of machine learning techniques for e-commerce product recommendation systems. *International Journal of Innovations in Science and Technology*. https://doi.org/10.33411/ijist/20257314751494

Tang, X. (2023). Algorithm design and optimization of data mining technology in reader service recommendation system. *2023 IEEE 15th International Conference on Computational Intelligence and Communication Networks (CICN)*, 80–86. https://doi.org/10.1109/cicn59264.2023.10402339

Tolety, V., & Prasad, E. (2022). Hybrid content and collaborative filtering based recommendation system for e-learning platforms. *Bulletin of Electrical Engineering and Informatics*. https://doi.org/10.11591/eei.v11i3.3861

Ugendhar, G., Kavya, K., Vishwak, P., Sanjeevi, P., & Rao, S. (2025). Personalized e-learning course recommendation system. *International Journal of Scientific Research in Engineering and Management*. https://doi.org/10.55041/ijsrem42783

Wang, J. (2025). Design and implementation of personalized recommendation algorithms in adaptive learning systems. *Advances in Engineering Technology Research*. https://doi.org/10.56028/aetr.14.1.1741.2025

Wang, Y. (2025). Application of data science and machine learning algorithms in intelligent recommendation system. *International Journal of Computer Science and Information Technology*. https://doi.org/10.62051/ijcsit.v5n1.23

Widayanti, R. (2023). Improving recommender systems using hybrid techniques of collaborative filtering and content-based filtering. *Journal of Applied Data Sciences*. https://doi.org/10.47738/jads.v4i3.115

Zhao, Y., Jing, X., & Guo, H. (2024). Research on intelligent recommendation of computer course items combining augmented learning algorithms and data mining techniques. *Applied Mathematics and Nonlinear Sciences, 9*. https://doi.org/10.2478/amns-2024-0517