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RECOMMENDER SYSTEMS IN E-LEARNING: TRENDS, CHALLENGES, AND FUTURE DIRECTIONS

KAOUTAR ERRAKHA [1] ,AMINA SAMIH [2] ,ABDERRAHIM MARZOUK [3] , AYOUB KRARI [4]

[1,3] Computer, Networks, Mobility and Modeling Laboratory, University Hassan First,Settat, Morocco
[2] Artificial Intelligence Research and Applications Laboratory ,University Hassan First, Settat, Morocco
[4] Laboratory of Research Watch for Emerging Technologies , University Hassan First, Settat, Morocco
[1] kaoutar.errakha@uhp.ac.ma, [2]amina.samih@uhp.ac.ma, [3]abderrahim.marzouk@uhp.ac.ma ,
[4]ayoub.krari@uhp.ac.ma

ABSTRACT

Recommender systems enable personalized learning experiences in e-learning, which was previously unheard of. This survey describes the history and evolution of recommender systems and the methodologies and problems faced in contemporary e-learning. We consider classical approaches like collaborative filtering, content-based filtering, and hybrid models, as well as new approaches using deep learning, knowledge graphs, and XAI (explainable artificial intelligence). We also analyze problems like data sparsity, cold start challenges, system interpretability, and ethics. Emerging trends like adaptive learning and proactive context-aware recommendations are also discussed. Every aspect of the field is explained in this article, and it forms the basis for further insights and the impact these systems will have on education in the future.

Keywords: *Recommender Systems ;E-Learning;Personalized Learning;Context-Aware Recommender Systems (Cars);Explainable Ai (Xai);Deep Learning*

1. INTRODUCTION

Over the past few years, the rise of online education platforms has drastically changed the way education systems operate [1]. It has given students the ability to have an extensive range of materials available to them at any place or time. Unfortunately, having an abundance of available resources makes it difficult to find the right material that aligns with an individual's needs, their personal preferences, and the specific style they learn through [2]. To solve these problems, recommender systems (RS) have become some of the most effective means of personalizing the educational experience by recommending appropriate courses, reading materials, and activities for each learner individually. Traditional recommender systems, which are popular in areas like e-commerce or entertainment, have been modified with the use of collaborative filtering, content-based filtering, and hybrid models to suit e-learning environments [3] . Recently, improvements in Artificial Intelligence (AI) and Machine Learning (ML) have incorporated more advanced methods such as deep learning, knowledge graphs, and explainable AI (XAI)[4]. These new methods improve the effectiveness and clarity of the information provided in the recommendations [5]. However, recommender systems for online learning do face some problems, such as a lack of data, the freezing start problem, the ability to clarify recommendations, and ethical issues, such as prejudice and justice. Also, making sure that suggestions are in accordance with users' changing needs and learning objectives is an intricate process. Although numerous scholars have attended to the study of recommender systems, there is lack of a single document that provides discusses the needs of a comprehensive survey on e-learning. This paper sets outs to:

- Provide an overview of traditional and modern recommender system techniques in e-learning.
- Examine the impact of context-aware and explainable AI-driven recommenders.
- Identify key challenges and limitations in current e-learning recommendation systems.
- Highlight emerging trends such as adaptive learning, knowledge graphs, and immersive technologies.
- Offer insights into future research directions for improving recommender systems in education.

The remainder of this survey is structured as follows:

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- Section 2 presents the foundational concepts of recommender systems in e-learning.
- Section 3 discusses challenges and limitations.
- Section 4 highlights emerging trends and future directions.
- Section 5 concludes the article with final thoughts and research perspectives.

By providing a structured analysis of recommender systems in e-learning, this survey aims to contribute to the ongoing development of intelligent educational technologies that enhance personalized learning experiences**.**

2. FOUNDATIONS OF RECOMMENDER SYSTEMS IN E-LEARNING

Recommender systems (RS) in e-learning aim to personalize the learning experience by suggesting relevant courses, study materials, exercises, and other educational resources [6]. Unlike traditional recommendation domains such as e-commerce and entertainment, e-learning introduces unique challenges, including knowledge progression, learning styles, and educational goals [7]. To address these challenges, various recommendation techniques have been developed, ranging from classical filtering approaches to advanced AI-driven methods. This section provides a comprehensive overview of the foundational techniques used in e-learning recommender systems.

2.1 Traditional Recommender System Techniques

Traditional recommender systems rely on pattern recognition in learner behavior and content characteristics to generate suggestions. The primary techniques include collaborative filtering, content-based filtering, and hybrid approaches[8].

1) Collaborative Filtering (CF)

Collaborative Filtering is a widely used approach that makes recommendations based on similarities between users or items. The assumption behind CF is that learners who interacted with similar resources in the past will likely share preferences in the future [9].

There are two main types of CF [10]:

a. ***User-Based Collaborative Filtering***: This technique identifies learners with similar learning patterns and recommends content that their peers have interacted with.

❖ **Example**: If student A and student B have taken multiple courses in common, and student A enrolls in a new course, then that course may be recommended to student B.

b. ***Item-Based Collaborative Filtering***: Instead of focusing on learner similarities, this method finds relationships between learning materials.

❖ **Example:** If a majority of learners who completed "Machine Learning Basics" also took "Deep Learning Fundamentals," the system may recommend the latter to new students who finish the first course.

While CF is effective, it faces several challenges [11]:

✅ Pros: Learner engagement is considered, making recommendations relevant.

❌ Cons: Suffers from data sparsity (lack of interactions) and the cold start problem (difficulty in recommending for new users or new content).

2) Content-Based Filtering (CBF)

Content-Based Filtering recommends educational materials based on similarities between content and a learner's past preferences. It creates a profile for each learner using [12]:

- Text analysis techniques (TF-IDF, word embeddings) to extract keywords from course descriptions [13].
- Metadata such as difficulty level, subject category, and learning objectives to match with learner preferences [14].

❖ **Example**: If a learner frequently engages with courses on "Artificial Intelligence," the system may recommend materials on "Machine Learning" due to their related content.

✅ Pros: Personalized recommendations tailored to each learner.

❌ Cons: Cold start problem for new users and overspecialization, where learners receive recommendations only in narrow topics without diversity.

3) Hybrid Recommender Systems

Hybrid approaches combine multiple recommendation techniques to overcome the weaknesses of individual models. Common hybridization strategies include [15]:

- Weighted Hybrid Models: Assign different weights to CF and CBF to balance their impact.
- Switching Models: Use CF when sufficient user interactions exist and switch to CBF for new learners.
- Feature-Augmented-Models:Add characteristics information into the content based recommendation algorithms.

❖ **Example**: For instance, a system could provide suggested materials based on peer interactions through collaborative filtering and refine those suggestions through content-based filtering using the learner's skill history.

✅ Pros: Improves accuracy and diversity of recommendations.
❌ Cons: Higher computational cost compared to standalone CF or CBF.

2.2 Context-Aware Recommender Systems (CARS) in E-Learning

Classic recommender systems mainly rely on user-item exchanges, like ratings, clicks, or buying actions, to create recommendations. Still, in e-learning situations, learner preferences are not fixed and can be profoundly affected by situational factors such as time, place, device, cognitive load, and social context. Context-aware recommender Systems (CARS) [16]use these dynamic factors to increase personalization and improve learning results. Considering the context in which learning occurs, CARS can recommend appropriate adaptive learning resources, course outlines, or interactions that fit the learner's context.

Context-aware recommender Systems (CARS) increase the level of personalization by considering dynamic factors [17] like:

Table 1: Contextual Factors

Contextual Factor	Description
Learner Profile	Background knowledge, learning style, cognitive abilities.
Learning Environment	Device used (mobile/laptop), time of access, location.
Social Context	Peer interactions, group activities, collaborative learning.

Example: A learner studying at night might receive recommendations for short video lectures, while another using a mobile device may be directed toward interactive quizzes instead of lengthy PDFs.
✅ Pros: Changes suggestions dynamically according to the learner's needs.
❌ Cons: It is costly in terms of computing resources and sophisticated data manipulation.

To incorporate contextual factors into recommendations, several methodologies are employed [18]:

a. Pre-Filtering [19]

The system eliminates irrelevant information before implementing standard recommendation systems. For instance, a mobile learning application deems long lecture videos low priority and gives priority to short lessons when used on a smartphone.

b. Post-Filtering [20]

The system produces suggestions using standard methods and later improves them using data points. For instance, if a user is keen on written materials, the system will give preference to text-based courses even if videos were suggested first.

c. Contextual Modeling (Incorporating Context in the Recommendation Algorithm)

This perspective introduces complexities into the recommendation systems' model. For instance, A multi-layer perceptron neural network can use time, space, and a learner's past behavior to automatically make optimal material selection methods described so far take into account the trade-off between accuracy and efficiency in resource expenditure. Computational modeling is the least accurate, and most straightforward contextual modeling is the most accurate and costly. Context-aware

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recommender Systems (CARS) are an important milestone in e-learning development as they evolved from pre-determined suggestions to real-time and self-adjusting personalized recommendations[21]. Considering learner profiles, environment, sociocultural context, and cognitive state, CARS ensures optimum learner engagement, better information retention, and an enhanced learning experience.The biggest hurdles remain in managing data privacy, the cost of computing, and scant information exposure from the users. Reality where intelligent learning systems can make context-aware recommendations is very promising[22]. In the subsequent passage, we discuss the role of technology such as deep learning, knowledge graphs, and explainable AI in transforming personalization within e-learning [23].

.2.3 AI-Driven Advances in E-Learning Recommendations

E-learning recommendation systems have become notably bright due to rapid advancements in artificial intelligence. This improvement has made personalized, adaptive, and precise learning experiences possible. AI-powered recommenders use complex machine-learning models to optimize content suggestions, predict learning preferences, and analyze user interactions. These accomplishments fall under three broad headings [24] :

A. Deep Learning-Based Recommender Systems

Deep learning models have transformed recommender systems by automating the identification of complex learner behavior patterns and content interactions. Unlike classical methods such as collaborative filtering or content-based methods, deep learning methods deal with all kinds of complex and disorganized educational data, including but not limited to lecture videos, texts, and students' conversations[25].

Key Deep Learning Approaches: [26]

Neural Collaborative Filtering (NCF): : These systems are more sophisticated than regular Collaborative Filtering Systems Enhanced with Multi-layer Perceptron Deep Learning neural networks, and learn user-item interactions better. Instead of simple matrix factorization approaches, NMF builds multiple s to capture complex non-linear relationships, leading to better recommendations.

Example : a system can recommend courses based on enrollment, rating, time spent on learning materials, and even participation in class discussions.

Recurrent Neural Network Classifier (RNN): RNNs use sequences with context as input; hence, they are designed to work with a sequence of a learner's study habits. They are highly suitable for anticipating future study requirements from past actions.

Example : A student who takes a course in Data Structures is assumed to successfully complete the Algorithms, the well-anticipated next course in a sequence of topics coordinated by an RNN model.

Transformers such as BERT and GPT: These types of Neural Networks, specialized in multitasking, require context to analyze spoken or written natural language. Hence, they are helpful in understanding and interpreting educational materials, including student requests and forum contributions.

For example, a forum powered by a transformer can scan discussions and recommend video tutorials and reading materials based on learners' unique struggles with "Bayesian Statistics.".

✅ Pros:Capable of processing diverse and unstructured educational data (videos, texts, assessments, discussions).Can identify deep relationships between learning materials and learner preferences.Highly accurate predictions improve the personalization of recommendations.

❌ Cons:Require large datasets and substantial computational power.Can act as "black boxes," making it difficult to interpret recommendations.

B. Knowledge Graph-Based Recommender Systems

Knowledge graphs provide a structured representation of educational content by mapping relationships between concepts, courses, and learning objectives[27]. Unlike purely data-driven models, knowledge graphs enhance explainability by making explicit connections between learning topics. A knowledge graph consists of nodes (educational entities like courses, topics, and

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learning outcomes) and edges (relationships between them). For example, a graph might show that: (i) **Linear Algebra** is a prerequisite for Machine Learning. (ii) **Object-Oriented Programming** is connected to Software Engineering. By integrating learner interactions into this structure, recommendations can be generated based on logical progressions in learning paths [28].

Applications in E-Learning:[29]

Recommendations Based On Prerequisites: Suppose a student plans on taking up "Neural Networks" the system may advise him to take "Calculus" and "Probability Theory" beforehand. "…the system may advise…", "…suggest reviewing…", and "...the system might… " are all examples of the same thing, which is sentence structure variation along with the use of synonyms. *Concept-Based Personalization*: In case the student has performed well in "Cybersecurity Fundamentals," the system may recommend moving on to "Ethical Hacking" or "Cryptography." Semantic-Based Search & Discovery: Enables learners to navigate through familiar topics and their linkages non-linearly rather than through a predefined course outline.

✅ Pros: Makes test justification more effective by intervening with clear, reasoned links. It makes "concepts and levels" learning hierarchies more logical, organized, and accurate. Provides opportunities for completing more accurate knowledge exploration and discovery.

❌ Cons: The system is time-consuming because it requires some automation or complete manual effort. Adapting to the changing curricula is problematic because it requires regular maintenance to remain relevant..

C. Explainable AI (XAI) in E-Learning Recommendations

In academic environments, openness and confidence in AI-supported suggestions are very important. Explainable AI (XAI) seeks to improve the interpretability of recommendation systems by explaining why a recommendation was offered [30].

Key Techniques in XAI for E-Learning:

- **Features Analysis [31]**: This allows the system to highlight the most important components it bases its recommendations on. For example, the system could state, "Advanced Python programming was recommended because the learner passed the 'Introduction to Python' and 'Data Structures' courses quite well."
- **Visualization Tools [32]**: Knowledge graphs, heatmaps, and attention maps display the links of the recommended content to the learners, the educators, and the students.
- **User Control Mechanisms [33]**: These mechanisms enable students to set their preferences, such as prioritizing practical project-based courses over theoretical courses [34].

Example Use Case: Rather than suggesting only "Neural Networks," an XAI-powered system would justify its recommendation: *"This course is recommended because having done 'Linear Algebra' and 'Machine Learning Fundamentals,' you will have found this course very helpful. 'So do most students with the same background.' "*

✅ Pros: Students are more likely to trust and rely on AI recommendations; teachers understand how XAI feature suggestions correlate with their teaching objectives and prepare suitable learning activities; and students make better decisions regarding their educational directions.

❌ Cons: Combining recommendable and explainable XAI can be complicated. The use of XAI strategies often means extra work.

Figure 1 shows the development of the recommendation system strategies in e-learning through periods. The histogram contrasts the older recommendation techniques, such as collaborative and content-based filtering, with the newer, more advanced techniques of context-aware and explainable recommendation systems. The trend shows more significant use of context-aware recommendations, which tailor learning experiences to specific situational parameters, and explainable artificial intelligence, which improves the trust and transparency of the recommendations offered. Such progress indicates great attention to adaptive and intelligent systems in digital education.

especially in the educational realm, where privacy and confidentiality are critical.

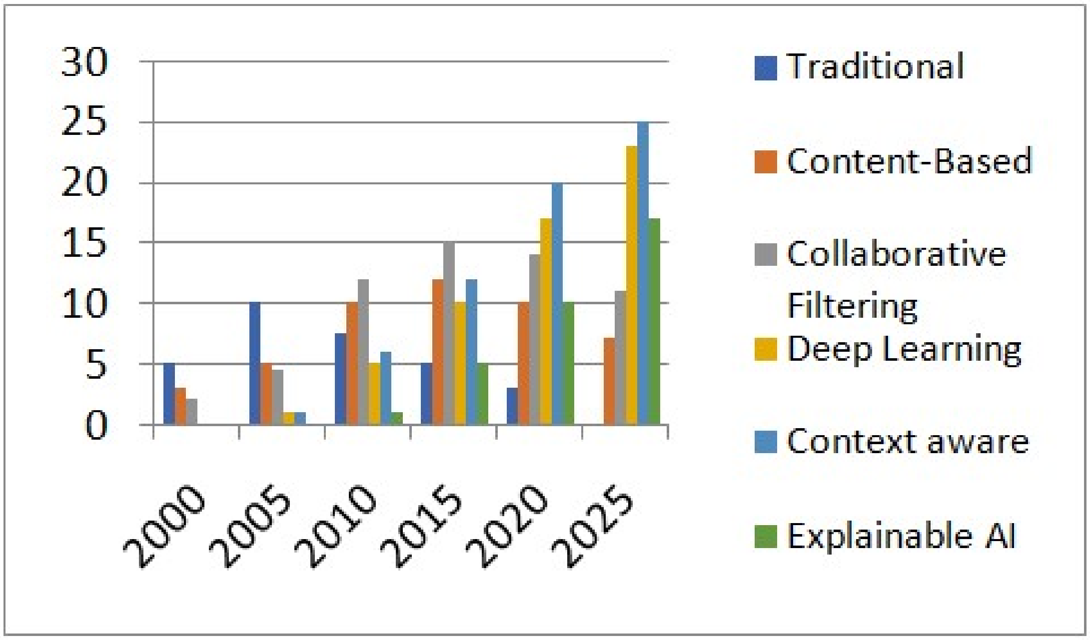

Figure 1 : Evolution of recommender systems in e-learning

3. CHALLENGES AND FUTURE DIRECTIONS IN E-LEARNING RECOMMENDATION SYSTEMS

Despite the significant advancements in e-learning recommendation systems (RS), several challenges remain. These challenges range from data privacy issues to the limitations in the generalization of models across diverse learning contexts. As e-learning continues to evolve, new technologies and methodologies will be required to address these obstacles and enhance the overall learning experience.

3.1 Challenges in E-Learning Recommendation Systems

A. Data Privacy and Security

One key issue with e-learning systems is the protection of sensitive information. Recommender systems can make accurate predictions based on sensitive learner data such as PII, behavioral patterns, and other significant learning activities. This information is considerably sensitive,

Possibility of Data Leakage: The use of AI and machine Learning increases the likelihood of breaching sensitive data and can result in the unethical exploitation of student information.

Legal Obligations: Sustaining legal instruments concerning international data protection, such as GDPR or FERPA, is challenging when recommending personalized e-learning content based on vast amounts of collected data..

B. Model Interpretability and Transparency

Despite the high accuracy provided by deep learning-based mechanisms, they are hardly interpretable. Most AI models are complex and non-transparent, making it hard for either an educator or student to know why specific recommendations are being made.

Trust and Acceptance: In the absence of recommendations explanations, both teachers and students might have trust issues with the system thus compromising its usefulness.

Explainability vs. Accuracy: Maintaining a middle ground between the performance of AI models and transparency in the educational setting is still a challenge. Although XAI techniques are proving to be useful, the problem is not yet resolved.

C. Handling Diversity in Learner Profiles

E-learning systems ought to accommodate students with different cultures, learning styles, cognitive skills, and levels of prior knowledge.

Personalization Complexity: Developing a recommendation system that performs well on a global student's diversity is a complex problem.

Learner's Learning Context: Differences in surroundings, such as learning while mobile versus learning with a computer, may require variations in content, delivery, and learning modes.

D. Computational Resources and Scalability

Even though deep learning and alternative AI frameworks offer greater precision in recommendations, they are more resource-intensive and expensive, particularly for enormous datasets.

- ✓ *Resource Limitations*: Most academic institutions, particularly in developing countries, may lack the necessary computational infrastructure to support the existence of such intricate systems.
- ✓ *Sustainability Concerns:* The growth in the number of users and courses in e-learning systems creates increased needs that are difficult to manage by augmenting recommendation systems .

3.2 Future Directions in E-Learning Recommendation Systems

A. Federated Learning for Privacy-Preserving Recommendations

Federated Learning allows a singular model to train indiscriminately to various decentralized devices, like learner smartphones or laptops. This form of machine learning is unique because it does not necessitate sharing sensitive data with a central server. Learner's personal information is stored in one single \device aiding in protecting privacy concerns. Furthermore, it addresses data privacy in e-learning systems, a high priority. Tracking and monitoring the learner's interactions can make unique recommendations without invading privacy, enabling real-time personalization.

B. Enhanced Hybrid Recommender Systems

Combining multiple suggestions is advantageous because hybrid recommender systems surpass the usual shortcomings of singular approaches. A better hybrid model can be constructed, as filtering users by inclination and qualifying services or merging a deep understanding of the material with extensive cognitive frameworks would produce both variety and precision.Recommended, Differently: Users are given a wide range of more substantial suggestions because the model combines different recommendation strategies to take advantage of comprehensive learning by more than one type of learner.

Hybrid Context Systems: Better personalization and adjustment of recommendations could come from combining some contextual factors, such as time and location, with more advanced blending recommendation techniques.

C. Explainable AI (XAI) Advancements

Even though XAI techniques have advanced greatly, more work needs to be done because users are concerned about how much insight an AI-powered recommender system provides to educators and learners.

- ➢ *Improved Interpretability*: Future studies will probably focus on enhancing the comprehensibility of AI-driven models, which will make them more user-friendly for educational stakeholders.
- ➢ *Explanatory Systems with User Interaction*: Upcoming systems will most likely allow users to interact with visualizations, increasing trust and user acceptance..

D. Incorporating Affective Computing

Affective computing pertains to technology that uses artificial intelligence to help understand and interpret human emotions. It becomes important in e-learning systems to detect students' emotional states, such as confusion, frustration, and engagement so that appropriate recommendations can be rendered at the appropriate time.

Emotion-Aware Recommendations: With the incorporation of affective computing, recommendation systems no longer need to base engagement on cognitive factors alone but also on the learners' emotions, which may facilitate the quality of learning and engagement.

E. Reinforcement Learning for Dynamic Adaptation

Reinforcement Learning (RL) is a branch of machine learning in which an agent interacts with an environment and learns over time the best routines to accomplish a goal. Recommendation systems are powered through RL and change and update according to the learner's actions.

- Adaptive Systems: RL helps increase recommendation systems' capabilities to be more accurate since it learns from learner interactions and adjusts its suggestions based on feedback.
- Long-Term Learning Goals: RL can also assist in recommending materials geared toward achieving a learner's goals over a longer time frame, making the system more responsive to the learners' changing needs..

F. Multi-Modal Learning Approaches

Multimodal learning combines different types of forms. For instance, videos, audio, and text materials are all integrated into one recommendation system. With this approach, learners are provided with the best content for their various preferred forms of information intake.

- ✓ *Integration of Learning Styles:* A student who has difficulty reading may benefit from listening to or watching learning material, whereas the student who likes reading will be directed to PDF or e-books.
- ✓ *Flexibility Features Of Multimodal Systems*: Multimodal systems improve the learning experience by accommodating a more excellent range of learning styles.

4. EMERGING TRENDS AND FUTURE DIRECTIONS IN E-LEARNING RECOMMENDER SYSTEMS

For the e-economy, integrating AI approaches in context-aware systems contributes significantly to e-learning recommenders as it is the most recent innovation. While most recommender systems relied on collaborative filtering as well as content-based techniques, the work done here demonstrates the shift in how learner profiles, emotional states, and social interactions serve as holistic variables to a learner's context. This dramatically improves the personalization and precision of recommendations. Context-aware systems expand on existing works and shed new light on how these elements can change content recommendations in real-time. The research draws attention to the context's capacity to determine suggestion systems' accuracy.

The incorporation of hybrid recommender approaches signifies an advancement from traditional systems. Although many previous works focused on single recommendation techniques, we build on this work by incorporating deep learning, content-based, and context-aware filtering techniques to build elaborate systems. This hybrid method overcomes several challenges faced by traditional recommendation systems, such as the cold-start problem and data sparsity. This combination of techniques makes our research more comprehensive and adaptable to personalized learning for different educational scenarios.

Besides, our work adds to the knowledge literature by introducing reinforcement learning to e-learning recommender systems. Reinforcement learning allows for adjusting recommendations in real time based on learner responses, providing a more personalized experience. Although some scholars have used reinforcement learning in other disciplines, it is not sufficiently utilized in e-learning systems. We try to fill this gap by showing how reinforcement learning enhances content engagement, retention, and overall learner satisfaction by constantly tailoring content based on students' interactions with the system.

Our work on cross-domain and lifelong learning recommendations begins where existing research finishes. As learners start interacting with material from different fields, a single-domain basis of traditional recommender systems becomes obsolete. We elaborate on how e-learning RS can continue to evolve to support lifelong learning by providing recommendations over the entire educational history of a learner. It solves learners' formal education concerns and professional and personal development. Our research addresses e-learning system recommenders of the future in these other domains and stages of a career as flexible and powerful instruments of ongoing education.

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Multiple studies have been done on the technical side of the recommendation algorithms. However, not much focus is placed on ethical concerns AI recommenders face, such as privacy, bias, data transparency, etc. Our research addresses ethics within AI by deeply exploring how to ensure fairness, transparency, and trust in the algorithms and, subsequently, responsible education through AI in highly neglected areas. This is a step towards implementing recommenders in education, an area that literature still undercovers to IP. Our work seeks to provide details on using context and AI-driven technologies within e-learning recommenders while creating active learning scenarios. In the meantime, advanced technologies like gaming and entertainment are flooded with new applications, but these primitives remain relatively young within the bounds of education. Thus, there is great potential for combining these novel technologies with learning ecm and instructional design, placing learners into the very heart of the matter. Our research creates possibilities for deeper engagement with the material through immersive technology and AI-based recommenders. We aim to employ context-aware and AI-based learning to promote learner engagement on an entirely different level. As humanity faces heightened data stimulus, we lay the groundwork for further inquiry into how to tackle the issue of tailoring learning paths in a highly personalized way. Table 1 provides a summary of the comparison between the different approaches.

Table 1:Comparison Of Different Approache

Approach	Advantages	Disadvantages	Data Usage
Context-Aware Recommender Systems in E-Learning	Offers contextual recommendations suitable for the learner's current situation Consider contextual factors such as time, place, skill level	Needs extra contextual information to be gathered (temporal, geo, emotional, etc.) -Complex contextual data handling	Works with behavioral, temporal, geo, and emotional data to modify recommendations in real time
Traditional Recommender System Techniques	Simple to implement. - Works well with an uncomplicated data system and simpler context	- Omits immediate context. - Not adaptable to dynamic learning contexts	Uses historical interactions database (learn history, clicks, ratings)
AI-driven Innovations in Recommendations for E-learning	Can personalize in real time using machine learning processes. - Considers pluralistic complex data for better recommendations	- Imposes high data and processing power requirement. - The models can be 'Black boxes' not open for interpretation	Makes use of behavioral data together with other data such as navigation, engagement, and performance to make real time recommendation changes.

5. CONCLUSION

The latest improvements in AI for contextualized design and XAI have reshaped the personalization of SOLE through online learning recommender systems. Recently, numerous context factors, including the learner's profile, learning environment, and social context, can be provided in real-time. The application of deep learning together with knowledge graphs has significantly enhanced the accuracy of these recommendations, making learning experiences highly individually tailored and dynamic.

Still, some issues remain. The management of data privacy and biases in AI algorithms continue to be important concerns that can damage trust and integrity in learning activities. In addition, the issue of responsible design of AI systems poses ethical challenges regarding their deployment in such a sensitive area as education.

Therefore, although the advancement of technology is likely to revolutionize personalization of online learning, equally sophisticated governance frameworks are needed so that these systems are functional, transparent, just, and ethical. To reap the most benefits and mitigate the harm that comes with employing AI, clear parameters on how it can be ethically used in education need to be made as soon as possible.

To sum up, the possibilities that AI and recommender systems offer in the context of online learning are astonishing; however, need for educational institutions to address the ethical, technical, and governance issues is imperative to achieve them.

REFERENCES:

[1] S. Reddy, I. Labutov, and T. Joachims, "Latent Skill Embedding for Personalized Lesson Sequence Recommendation," arXiv preprint arXiv:1602.07029, 2016.

[2] N. Hoić-Božić, M. Holenko Dlab, and J. Mezak, "Using Web 2.0 Tools and ELARS Recommender System for E-Learning," in Proceedings of the International Conference on E-Learning, La Laguna, Tenerife, 2014.

[3] J. M. Kleinberg, "Challenges in Recommender Systems," in Proceedings of the 15th ACM Symposium on Principles of Database Systems (PODS'16), 2016.

[4] El Naqa, I., & Murphy, M. J. (2015). What is machine learning?. In Machine learning in radiation oncology: theory and applications (pp. 3-11). Cham: Springer International Publishing.

[5] Bhatt, B., Patel, P. J., & Gaudani, H. (2014). A review paper on machine learning based recommendation system. International journal of engineering development and research, 2(4), 3955-3961.

[6] Samih, A., Ghadi, A., Fennan, A. (2023). The Impact of Covid 19 on Recommendation Platforms. In: Kacprzyk, J., Ezziyyani, M., Balas, V.E. (eds) International Conference on Advanced Intelligent Systems for Sustainable Development. AI2SD 2022. Lecture Notes in Networks and Systems, vol 713. Springer, Cham. https://doi.org/10.1007/978-3-031-35248-5_3

[7] Samih, A., Hamane, Z., Ghadi, A., Fennan, A. (2024). Health Recommender Systems. In: Ezziyyani, M., Kacprzyk, J., Balas, V.E. (eds) International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD'2023). AI2SD 2023. Lecture Notes in Networks and Systems, vol 904. Springer, Cham. https://doi.org/10.1007/978-3-031-52388-5_25.

[8] Kulkarni, P. V., Rai, S., & Kale, R. (2020, January). Recommender system in elearning: a survey. In *Proceeding of International Conference on Computational Science and Applications: ICCSA 2019* (pp. 119-126). Singapore: Springer Singapore.

[9] Su, X., & Khoshgoftaar, T. M. (2009). A survey of collaborative filtering techniques. Advances in artificial intelligence, 2009(1), 421425.

[10] Li, B. (2011, November). Cross-domain collaborative filtering: A brief survey. In 2011 IEEE 23rd International Conference on Tools with Artificial Intelligence (pp. 1085-1086). IEEE.

[11] Koren, Y. (2009, June). Collaborative filtering with temporal dynamics. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 447-456).

[12]Petter, S., Fichtner, M., Schönig, S., & Jablonski, S. (2022). Content-based Filtering for Worklist Reordering to improve User Satisfaction: A Position Paper. In ICEIS (2) (pp. 589-596).

[13]Joachims, T. (1997, July). A probabilistic analysis of the Rocchio algorithm with TFIDF for text categorization. In ICML (Vol. 97, pp. 143-151).

[14] Ibrahim, O. A. S., Younis, E. M., Mohamed, E. A., & Ismail, W. N. (2025). Revisiting recommender systems: an investigative survey. Neural Computing and Applications, 1-29.

[15]Samih, A., Ghadi, A., & Fennan, A. (2020, December). Translational-randomwalk embeddings-based recommender systems: a pragmatic survey. In International Conference on Advanced Intelligent Systems for Sustainable Development (pp. 957-966). Cham: Springer International Publishing.

[16]Mateos, P., & Bellogín, A. (2025). A systematic literature review of recent advances on context-aware recommender systems. Artificial Intelligence Review, 58(1), 1-53.

[17] ERRAKHA, K., SAMIH, A., MARZOUK, A., & KRARI, A. (2024). SURVEYING THE BLACK BOX: AN OVERVIEW OF CONTEXT-AWARE RECOMMENDER SYSTEMS. Journal of Theoretical and Applied Information Technology, 102(21).

[18] Ding, Z. (2025). Design and evaluation of an English speaking recommender system using word networks and context-aware techniques. Entertainment Computing, 52, 100920.

[19] Du, J., Hew, K. F., & Zhang, L. (2025). Designing a recommender system to promote self-regulated learning in online contexts: A design-based study. Education and Information Technologies, 30(2), 2389-2428.

[20] Yu, P., Xu, Z., Wang, J., & Xu, X. (2025). The application of large language models in recommendation systems. arXiv preprint arXiv:2501.02178.

[21] Anand, V., & Maurya, A. K. (2025). A survey on recommender systems using graph neural

network. ACM Transactions on Information Systems, 43(1), 1-49.

[22] Samih, A., Ghadi, A., & Fennan, A. (2022, March). Hybrid movie recommender system based on word embeddings. In International Conference on Networking, Intelligent Systems and Security (pp. 454-463). Cham: Springer International Publishing.

[23] Mezni, H., Benslimane, D., & Bellatreche, L. (2021). Context-aware service recommendation based on knowledge graph embedding. IEEE Transactions on Knowledge and Data Engineering, 34(11), 5225-5238.

[24]Jain, A., & Pandita, D. (2024, November). AI-Driven Resource Allocation in E-Learning During Internet Fluctuations. In 2024 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT) (pp. 541-546). IEEE.

[25] Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. ACM computing surveys (CSUR), 52(1), 1-38.

[26] Mu, R. (2018). A survey of recommender systems based on deep learning. Ieee Access, 6, 69009-69022.

[27] Guo, Q., Zhuang, F., Qin, C., Zhu, H., Xie, X., Xiong, H., & He, Q. (2020). A survey on knowledge graph-based recommender systems. IEEE Transactions on Knowledge and Data Engineering, 34(8), 3549-3568.

[28] Wang, S., Hu, L., Wang, Y., He, X., Sheng, Q. Z., Orgun, M. A., ... & Yu, P. S. (2021). Graph learning based recommender systems: A review. arXiv preprint arXiv:2105.06339.

[29] Wu, S., Sun, F., Zhang, W., Xie, X., & Cui, B. (2022). Graph neural networks in recommender systems: a survey. ACM Computing Surveys, 55(5), 1-37.

[30] Luckyardi, S., & Rahman, L. (2021). Application of e-learning system in the world of education. Jurnal Teknologi Informasi Dan Pendidikan, 14(1), 47-52..

[31] Tan, J., Xu, S., Ge, Y., Li, Y., Chen, X., & Zhang, Y. (2021, October). Counterfactual explainable recommendation. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management (pp. 1784-1793).

[32] Brdnik, S., Podgorelec, V., & Šumak, B. (2023). Assessing perceived trust and satisfaction with multiple explanation techniques in XAI-enhanced learning analytics. Electronics, 12(12), 2594.

[33] Chen, X., Zhang, Y., & Wen, J. R. (2022). Measuring" why" in recommender systems: A comprehensive survey on the evaluation of explainable recommendation. arXiv preprint arXiv:2202.06466.

[34] Ooge, J., Kato, S., & Verbert, K. (2022, March). Explaining recommendations in e-learning: Effects on adolescents' trust. In Proceedings of the 27th International Conference on Intelligent User Interfaces (pp. 93-105).