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Transforming learning through artificial intelligence: Evolution of guided learning systems

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Abstract

Artificial intelligence powered learning systems are transforming the learning landscape by using advanced algorithms and comprehensive data to deliver a highly personalized and adaptive learning experience. These systems analyze learner behavior, preferences, and outcomes at the macro and micro levels. This allows them to provide tailored content recommendations. adaptive assessment and tailored learning paths. Adaptive systems are those that are able to continuously learn from user interactions and feedback. An AI-powered recommendation system can dynamically adjust recommendations. This ensures that learners receive the most relevant and effective learning resources at all times. These advanced AI models can create personalized content, place interactive learning materials and even simulate a human-led teaching and learning experience. For example, chatbots and AI-powered virtual assistants can engage learners in understanding learner preferences, deciphering learning styles, answering questions and providing real-time feedback. effectively simulating a human teacher. In addition, generative AI can personalize, summarize and modify existing content to customize it based on individual learning capabilities, patterns, preferences, and achievement levels. ensuring that each learner receives a truly customized learning experience as AI continues to evolve.

Keywords: Artificial Intelligence (AI); Recommended Learning Systems; Personalization; Creative AI; Data-Driven Insights; Adaptive Algorithms; Content creation

1. Introduction

Artificial intelligence (AI) is transforming employee learning and development by delivering creative, personalized experiences. An effective AI-powered recommendation system changes traditional learning methods and creates customized learning paths. which address the gaps and preferences of individuals (Rukadikar & Khandelwal, 2023). These systems analyze factors such as behavior, delivery, and learning styles to provide an experience that adapts to reality.

Within the learning ecosystem, there are 2 types of systems:

- Learning management systems (LMS), which are primarily concerned with managing and delivering all learning content online.
- Learning Experience Platforms (LXP), which are aimed at providing a holistic and personalized learning experience to the user, by integrating personalization, social learning, gamification and analytics.

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The LMS and LXPs use machine learning algorithms to analyze employee performance inputs, learning preferences, and the requirements of the organization. They can then recommend relevant content, adjust the pace of learning, and provide real-time feedback, significantly enhancing the effectiveness of training programs (Xu et al., 2021). For instance, recommender systems that perform content based filtering can dynamically create customized learning paths, ensuring that employees receive content at their own pace and level of understanding (Onesi-Ozigagun et al., 2024). Learning experience platforms are able to use collaborative and content based filtering.

The customizable nature of these platforms and interfaces entails the creation of personalized learning paths, identifying strengths and weaknesses to focus on areas requiring improvement while reinforcing existing knowledge. The tailored approach accommodates diverse learning needs, offering alternative content formats to address various learning modalities and accessibility requirements. Integrating AI in adaptive learning systems has shown significant potential in improving learning outcomes. AI algorithms are helping to personalize the learning experience by optimizing the learning path. increase participation and improve academic performance (Gligorea et al., 2023).

Artificial intelligence recommendations extend beyond content delivery to facilitate collaborative learning, assessment, and feedback mechanisms. AI-enabled systems and platforms can use employee usage data and employee responses to provide feedback and insights on learning progress and course effectiveness (Onesi-Ozigagun et al., 2024). The system is designed in a way that allows for continuous improvement and adjustment of learning strategies.

This is because these systems are continually evolving. Therefore, these systems can democratize high-quality personal education worldwide. By addressing educational gaps and meeting unique learning needs. Artificial intelligence-powered recommendations have the power to improve learning opportunities. and offer access to customized and effective learning experiences for employees served in the community.

2. The Evolution of Recommended Learning Systems

The evolution of recommended learning systems has indeed undergone a significant transformation, moving from traditional rule-based approaches to AI-enhanced systems. This shift has been driven by advancements in artificial intelligence, machine learning algorithms, and the augmentation of computational power (Radanliev, 2024). Traditionally, rule-based systems depended on artisanal knowledge and had to be transformed from time to time based on rule-augmentation. Sophistication in rules meant that nested logic had to be created within the rule based systems. Statistical learning techniques and neural networks trained in large datasets helped bridge the gap by classifying learners and recommending content that was in line with their classification. There were 2 main techniques used by recommendation engines to perform filtering:

Collaborative filtering: leverages user-item interactions and similarities among users to make recommendations (Anava et al., 2015; Kumar et al., 2023). Collaborative filtering enabled recommender systems suffer the limitation of having gaps in data, due to presence of items that have had low user interactions. Similarly, collaborative filtering would use new user data

Content-based filtering: recommends items based on item-attributes and user's past preferences, assuming users will like items similar to those they've previously enjoyed (Ghazanfar & Prugel-Bennett, 2010).

One of the downsides of content-based filtering is that it may recommend content that is very similar to the user's past preferences, limiting the diversity of choices for user (Sollenborn & Funk, 2002).

The advent of deep learning and more advanced AI-enabled learning systems has gained traction due to the ability to deliver personalized learning as well as adapt to learner needs (Kabudi et al., 2021).

AI enabled learning experience platforms have the ability to analyze large amounts of student data in real time. Artificial intelligence helps enhance content filtering, recommendations, search, tagging and personalization (Pendyala & Lakkamraju, 2024), enabling targeted, customized learner experience, leading to increased learner satisfaction (Ayeni et al., 2024)

2.1. Traditional Rule-Based Systems

Traditional recommender systems followed rule-based algorithms and simple collaborative and content filtering methods. Key characteristics included (See: Figure 1(a) and (b))

- **Dependence on Explicit Data:** Systems require explicit user input, such as ratings or search histories, to function effectively.
- **Limited Adaptability:** They were unable to dynamically respond to changing user behaviors or preferences in real time.
- **Narrow Personalization:** Recommendations were constrained by predefined rules, often leading to generic suggestions.

2.2. AI-Enhanced Recommender Systems

AI has introduced transformative capabilities that address the limitations of traditional systems. Key improvements include (See: Figure 1(a) and (b)).

2.2.1. Data-Driven Insights

- **Macro-Level Data Analysis:** AI analyzes large datasets, including demographic information, historical learning trends, and industry-specific requirements, to predict and recommend relevant content.
- **Micro-Level Personalization:** Individual user behaviors, preferences, and interaction patterns are captured to tailor recommendations uniquely to each learner.

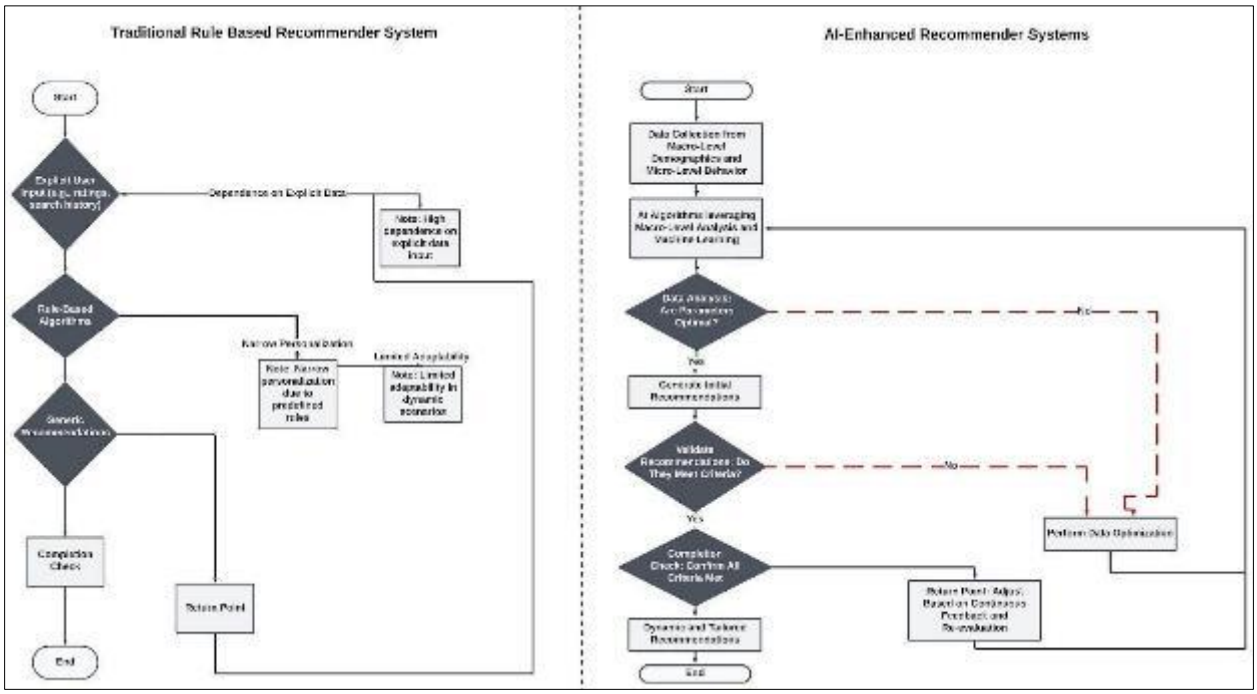

Figure 1(a) and (b) Comparison between Traditional Rule based recommender System Vs AI- Enhanced Recommender's system

2.2.2. Replicating Human Behavior

AI systems can simulate human decision-making processes, enabling recommendations that align closely with individual learning needs. Techniques such as neural networks and reinforcement learning help mimic the cognitive processes of educators and mentors. AI Agents can further enable actions being performed such as auto-enrollments based on user requests.

2.2.3. Reduced Learner Input

With artificial intelligence, systems require less input from learners and can be adaptive. Algorithms classify learner profiles based on implicit data, such as time spent on topics, assessment results, and engagement levels, streamlining the personalization process.

3. The Role of Generative AI in Recommended Learning

Generative AI has transformed how educational content is created and delivered. Unlike traditional models that are forced to rely on pre-existing course content, generative AI can help with a lot of use-cases. In this study, we will look at **BERT (Bidirectional Encoder Representations from Transformers),** which is a powerful natural language processing model that can significantly enhance Learning Experience Platforms (LXPs) by improving content recommendations, personalization, search functionalities, and knowledge retrieval.

Below are some use-cases that BERT can help with (Masciari et. al, 2024):

- **Content recommendation enhancement**: BERT helps analyze user queries, learning histories and course metadata to enable a personalized and context-aware recommendation experience. By understanding the context of content metadata and correlating that with user interests, BERT is able to enable semantic matching, which also helps with tagging. By processing user feedback, history of all searches and learning preference data from users, personalization of content is achieved.
- **Search enhancement**: With the semantic matching use-case, BERT-powered search is able to understand the intent behind the search rather than match just the keywords. This algorithm is also able to suggest relevant topics for the user based on incomplete or ambiguous queries - this helps user expand their queries to yield relevant results.
- **Personalized learning paths**: BERT's most advanced application in learning experience platforms lies in improving the user's personalized experience by predicting their next best course of action. The algorithm analyzes learner's usage metrics, topics searched and content rated to generate learner journey and next best learning module. Advanced personalization includes studying skill gaps, learning objectives to enable an adaptive learning experience, which consists of adaptive assessments and learning paths.
- **Automated Content Tagging**: The algorithm automates metadata tagging at the source for courses, articles, videos, enabling content discoverability and accessibility in LXPs. This could either happen within the CMS or at the backend layer of the LXP. Automation in content tagging includes assignment of categories and tags to content, extraction of key themes from course metadata as well as clustering of courses based on content based filtering.
- **Virtual Assistants for Learning**: AI enables development and deployment of chatbots that can assist with user queries either pertaining to content of courses or the entire experience itself. Additionally, the virtual assistant is also able to engage users in an interactive Q&A session to facilitate deeper and meaningful learning experience.
- **Learner Sentiment Insights**: By analyzing the learner sentiment through natural language processing, the BERT algorithm enables actionable course development based on feedback, course reviews and processing of learner comments and testimonials.

3.1. Create Content on Demand

In addition to use-cases mentioned above, using natural language processing (NLP) and machine learning models, creative AI systems can:

- **Aggregate content from multiple sources**: Combine information from multiple courses, articles, and datasets to create a comprehensive learning resource.
- **Create an Adaptive Curriculum:** Modular and flexible curriculum customizations are tailored to the specific needs of individual employees or groups.
- **Auto-create Assessments**: Based on the user interactions, their preferences, profile strengths and opportunities, assessments can be auto-generated and made adaptive
- **Timely Optional Customization:** Dynamically adjust content in response to user feedback. and ensure that learning materials are relevant and current.

For example, medical employees who want to understand the latest advances in AI in healthcare can request a course that combines journal articles, case studies, and expert insights with integrated learning modules in seconds.

3.2. Enhance User Interaction

Generative AI enables conversational interfaces where learners can pose questions and receive detailed, synthesized responses. For instance:

A learner interested in blockchain technology might receive a structured, multi-module course generated in real-time, integrating explanations, examples, and industry applications.

Additionally, interactive learning will ensure that the learner can provide responses which can be used by the AI engine to further refine its recommendations for the current user as well as users that pertain to the same classification

Interactive Q&A capabilities allow learners to dive deeper into specific aspects of a topic, creating a more engaging and exploratory learning environment.

3.3. Automate Content Creation for Institutions

Educational institutions and corporate training programs benefit from generative AI by:

- **Automating Course Development:** Institutions can quickly develop courses without requiring extensive manual effort from subject matter experts.
- **Reusing existing content:** Generative AI can organize and optimize existing resources into new formats, such as nanolearning modules. or interactive e-learning courses
- **Scaling up personalized learning:** AI-powered systems can engage large groups of employees while maintaining individual attention. This ensures that each participant receives content tailored to their specific goals and level of success.
- **Translation**: Enabling auto-translation of content into multiple languages as per audience need can reduce the need for third-party translation systems or manual translations, generating major operational efficiency

3.3.1. Improve Learning Analytics

Generative AI also contributes to improved analytics by creating a feedback loop. The content generated and consumed provides data that AI systems can analyze to:

- Identify knowledge gaps.
- Predict learning outcomes.
- Refine future content recommendations

By integrating generative AI, recommended learning systems improve on traditional recommender systems, enabling a dynamic, flexible, and learner-centric approach to education. Recommended learning is majorly boosted by the presence f

4. Examples of AI-Driven Transformations in Learning Systems

4.1. Example 1: Adaptive Learning Platforms

Platforms like Docebo, Coursera, LinkedIn Learning and edX integrate AI to provide personalized learning pathways. By analyzing user progress, these systems recommend courses, supplementary resources, and skill-building exercises that align with individual goals.

4.2. Example 2: AI-Powered Virtual Tutors

AI-powered virtual waiters, such as Duolingo's chatbot or Quizlet's AI assistant, offer customized suggestions and escape options. These systems adapt dynamically to learner learning. This ensures a personalized experience.

4.3. Example 3: Enterprise Learning Solutions

Learning experience platforms scalable for enterprises such as Degreed and Cornerstone leverage AI to map employee skills against organizational needs, recommending targeted training programs. Generative AI further enhances these platforms by creating bespoke training modules from company-specific data.

5. Challenges in AI-Enhanced Recommended Learning Systems

Challenges in AI-enhanced learning systems for organizations and employee development:

- Data Privacy: Balancing data utilization with employee privacy. Implementing robust protection measures, clear policies, and transparent practices.
- Algorithm Bias: Mitigating biases through diverse datasets, regular audits, and continuous improvement to ensure fair recommendations for all employees.
- Accessibility: Designing inclusive AI-driven platforms that accommodate diverse learning styles, disabilities, and cultural differences among employees.
- Integration: Seamlessly incorporating AI systems into existing learning frameworks, addressing potential resistance, and providing adequate training for HR and management.
- Scalability: Ensuring AI systems can handle increasing data volumes and users while developing cost-effective solutions for widespread implementation across the organization.

6. Conclusion

AI-based personalized learning systems have revolutionized employee training and development by leveraging advanced technology to create individually tailored learning experiences. These systems use artificial intelligence to create personalized experiences and machine learning algorithms to analyze content to deliver tailored content and recommendations by adapting to each learning style. AI-powered systems can greatly improve knowledge retention and maturity. Additionally, these systems can create dynamic content in real-time. and ensuring that learning materials are updated and relevant to the rapidly changing needs of brands (Rukadikar & Khandelwal, 2023).

While AI can significantly improve and aid in personalized learning, there are also many challenges to ensure its ethical and effective use. Privacy concerns must be carefully managed to protect learner privacy and maintain trust in the system. In addition, stakeholders should be alerted to identify severe algorithmic issues that may create Inaccurate or limit learning opportunities for some groups. Maintaining human participation and interaction in AI-based learning environments is also important to promoting critical thinking. creativity and social skills that cannot be fully replicated outside of automation. By addressing these concerns and continuing to develop AI-powered learning systems, organizations can create inclusive teaching experiences. effective and can be changed more This helps employees thrive in an increasingly knowledge-driven world (Rukadikar & Khandelwal, 2023).

6.1. Future Directions for AI in Recommended Learning Systems

Advanced AI applications within the program use a variety of methods to revolutionize the learning experience. Natural language processing enables complex interactions between learners and AI systems and leads to more natural and engaging teaching conversations. Cross-modal analysis integrates different types of data (text, audio, images) to enable a comprehensive understanding of learner engagement and learning styles. The dynamic adjustment option allows the AI system to adapt in real-time based on learner responses. This keeps the learning experience challenging but enjoyable for the user. Explainable AI models provide transparency in the decision-making process by enabling teachers and learners to understand the argument behind the recommendations and assessment.

Integrating these techniques creates a powerful ecosystem for individual learning. Individual teaching paths can be dynamically created around the unique strengths, weaknesses, and learning styles of each learner, enhancing the immersive learning experience. Recommender systems, powered with AI, have the ability to generate, curate, combine and summarize content for users. Together, these advances have resulted in a more efficient, engaging, and effective educational landscape, where AI serves as a powerful tool to enhance human teaching and learning skills.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare no conflicts of interest. The authors have contributed to this article in their personal capacity without the financial support or review of their employers. As such, the information and opinions in this paper attributable to the author are their own and do not necessarily reflect and are not endorsed by their employers.

Statement of ethical approval

Ethical guidelines were adhered to throughout the study.

Data Access Statement

Data supporting the findings of this study are available upon request.

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