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An Intelligent Personalized Learning Management System Using Artificial Intelligence And Neural Collaborative Filtering

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Abstract- Traditional Learning Management Systems (LMS) often provide the same educational materials to everyone, overlooking each learner's unique pace, interests, and achievements. This can lead to lower motivation and less effective results in education. In this paper, we introduce an innovative AI-powered Learning Management System that employs Machine Learning methods, particularly Neural Collaborative Filtering (NCF), to offer tailored learning suggestions. Our system actively examines learner actions, including how they engage with videos, perform on quizzes, express topic preferences, and track their overall progress, to create individualized learning journeys. By representing both learners and educational resources in a common hidden space, it effectively forecasts the most suitable content for each person. The LMS features an AI-powered assistant that functions like a personal tutor, crafting flexible learning plans and custom quizzes using live performance insights. As learners interact more with the system, the recommendation tool gets smarter, delivering suggestions that are timely, pertinent, and aligned with their objectives. It caters to diverse subjects such as coding, software creation, language acquisition, and hands-on project work. Through rigorous testing, we've shown that this method boosts learner involvement, refines recommendation precision, and enhances overall learning productivity when compared to conventional, unchanging LMS setups. The design is built to grow with demand, adjust to changes, and thrive in today's online learning landscapes.

Index Terms- Learning Management System, Artificial Intelligence, Neural Collaborative Filtering, Personalized Learning, Recommendation Systems, Adaptive Education.

I. INTRODUCTION

Learning Management Systems (LMS) have become a foundational component of contemporary education ecosystems. They provide digital infrastructure for sharing instructional materials, administering assessments, and tracking learner progress within a unified platform. With the steady growth of online and blended learning models, LMS platforms are now widely adopted across higher education institutions, corporate training programs, and independent learning initiatives. However, despite their extensive use, many current systems are primarily designed for content management and administrative oversight rather than for adapting to individual learning behaviours over time.

Learners differ substantially in background knowledge, learning speed, interests, and study preferences. While some individuals benefit more from visual content, others prefer interactive tasks or detailed written explanations. Traditional LMS platforms generally offer a fixed instructional pathway, delivering the same sequence of materials to all users. Such a uniform structure may limit engagement, especially for learners who require personalized pacing or additional academic support. When instructional pathways remain static, the system misses opportunities to enhance learning effectiveness for diverse users.

A further challenge lies in how learner interaction data are utilized. Contemporary LMS platforms capture extensive behavioural information, including viewing patterns, quiz performance, time allocation across topics, and navigation sequences. These data provide valuable insight into learner strengths, areas of difficulty, and levels of engagement. In many implementations, however, such information is used

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primarily for summary reports rather than to drive adaptive learning interventions. Consequently, learners often receive standardized content instead of recommendations tailored to their demonstrated performance.

Advances in Artificial Intelligence (AI) and Machine Learning (ML) present viable approaches for addressing these limitations. By examining behavioural data, intelligent models can identify patterns that indicate learning needs and predict which resources may be most beneficial for a given user. Embedding these techniques within LMS environments enables a transition from static delivery systems to adaptive platforms capable of supporting individualized progress. Within this framework, recommendation mechanisms play a critical role by guiding learners toward appropriate materials, exercises, and structured learning sequences.

Collaborative filtering techniques have previously been applied in educational recommendation contexts. However, traditional implementations may face limitations related to sparse interaction data and complex user–content relationships. Neural Collaborative Filtering (NCF) extends this approach by leveraging neural network architectures to capture non-linear relationships between learners and educational resources. This modeling flexibility is particularly valuable in dynamic learning settings where preferences and performance indicators evolve over time.

In this study, we develop and implement a Learning Management System that integrates Neural Collaborative Filtering within an AI-driven adaptive architecture to support personalized learning experiences. The platform monitors learner activities—including video engagement metrics, assessment outcomes, and navigation behaviours—and processes these signals to generate customized recommendations. Additionally, an embedded AI assistant serves as a virtual academic guide, proposing adaptive study plans, targeted practice exercises, and relevant resources when learning gaps are identified. Through this continuous feedback mechanism, the system aims to enhance learner motivation and promote self-directed study habits.

The proposed framework is designed to operate across diverse educational domains such as programming, software development, language instruction, and project-oriented training. Recommendations are adjusted according to domain-specific objectives and learner performance indicators, enabling flexibility across varied instructional contexts. This paper details the design principles, methodological framework, and evaluation of the proposed system. Section II reviews related literature, Section III outlines the system architecture and implementation methodology, Section IV presents experimental findings, and Section V concludes the study and discusses future research directions.

II. LITERATURE SURVEY

Recent research highlights the importance of personalization in Learning Management Systems (LMS) as a key factor in improving learner engagement and instructional effectiveness. Many existing LMS platforms are primarily optimized for distributing content and handling administrative functions, while offering limited mechanisms to adapt to differences in learner pace, prior knowledge, and preferred learning approaches. Studies consistently indicate that systems lacking adaptive capabilities may weaken motivation and participation, especially in online and blended learning contexts. To overcome these constraints, researchers increasingly investigate Artificial Intelligence (AI) techniques—including machine learning, learning analytics, and recommendation models—to construct learning environments that respond dynamically to user behavior. By examining interaction data such as assessment outcomes, navigation patterns, and time-on-task metrics, these systems can infer learning needs and provide targeted adaptive support. Empirical findings suggest that AI-enhanced LMS frameworks delivering personalized feedback and resources contribute positively to both learner satisfaction and academic performance.

Collaborative filtering remains a foundational method in recommendation system design and has demonstrated effectiveness across domains such as e-commerce, digital media, and online education. Within LMS environments, it operates by identifying relationships among learners with comparable behavioral patterns and using these similarities to suggest relevant materials. Early user-based and item-based approaches encountered limitations related to sparse interaction data, cold-start scenarios, and scalability in large populations. Matrix factorization techniques improved efficiency by mapping users and learning resources into shared latent representations. Nevertheless, conventional collaborative filtering struggles to represent the complex and evolving relationships characteristic of educational settings, where learner preferences shift over time. These challenges motivate the exploration of more expressive recommendation frameworks capable of modeling dynamic interactions.

Recent advances in deep learning have enabled Neural Collaborative Filtering (NCF), which extends recommendation modeling through neural network architectures. Unlike traditional matrix factorization, NCF captures non-linear relationships between learners and learning resources, improving predictive accuracy. Educational applications of NCF demonstrate its ability to recommend courses, activities, and assessments based on historical interaction patterns. Experimental studies report gains in ranking performance and user satisfaction when neural methods are employed. In addition, NCF models handle sparse datasets more robustly and can incorporate contextual features such as learner proficiency and engagement indicators. These properties position NCF as a strong technical foundation for scalable adaptive learning systems.

Learning analytics and predictive modeling represent another major direction in intelligent LMS research. Machine learning techniques are widely applied to forecast learner performance, identify students at risk of underachievement, and trigger early instructional interventions. Approaches such as decision trees, support vector machines, and neural networks analyze assessment data and behavioral signals to generate predictive insights. When integrated with recommendation mechanisms, these models enable continuous adjustment of learning pathways. Researchers note that such systems benefit both learners and instructors by delivering actionable feedback and performance analytics. Evidence from large-scale deployments indicates measurable improvements in retention and learning outcomes in adaptive LMS implementations.

Beyond recommendation and analytics, the integration of intelligent agents and virtual tutoring systems has attracted significant attention. These AI-driven assistants interact with learners in real time, offering guidance, explanations, and structured support. Studies suggest that virtual tutors can enhance motivation and promote self-regulated learning when combined with adaptive personalization strategies. They are particularly effective in guiding learners through customized study sequences and addressing emerging knowledge gaps. At the same time, practical challenges persist, including scalability, real-time processing requirements, and data privacy considerations. The system proposed in this work extends prior research by tightly coupling Neural Collaborative Filtering with an AI-based learning assistant to deliver scalable, data-driven personalization within LMS environments.

III. METHODOLOGY

The proposed Learning Management Framework follows a staged methodology that integrates Artificial Intelligence, Machine Learning, and Neural Collaborative Filtering to enable personalized learning. Rather than operating as a single linear pipeline, the framework consists of coordinated modules responsible for data acquisition, analysis, and recommendation generation. Learner interaction data is progressively transformed into adaptive suggestions that reflect individual progress. In addition to data-driven models, rule-based components are incorporated to maintain instructional consistency and contextual relevance. The architecture is designed to support scalability across multiple subject domains, including programming, application development, and language learning. Through the coordinated operation of AI agents, recommendation models, and performance analytics, the framework delivers continuous and focused support throughout the learning process.

A. Learner Data Collection and Preprocessing.

The initial stage involves collecting interaction data generated during routine system usage. This data includes enrolled information, video engagement duration, quiz attempts, assessment scores, navigation sequences, and time spent on learning activities. Because raw records may contain noise or missing values, a preprocessing step is applied to ensure reliability. Numerical attributes such as scores and engagement duration are normalized, while categorical features—including subject domain and resource type—are encoded for compatibility with machine learning algorithms. After cleaning and transformation, the data is stored in a structured repository that supports subsequent profiling and recommendation processes.

B. User Profiling and Feature Representation

Following preprocessing, the system constructs learner profiles by extracting behavioural and performance-related indicators. Each profile summarizes attributes such as topic proficiency, learning pace, assessment trends, and preferred content formats. Historical interaction records are converted into numerical feature vectors suitable for computational model. To reduce redundancy while preserving essential information, dimensionality reduction techniques are applied. These compact representations facilitate efficient comparison among learners and learning resources. The resulting profiles serve as inputs to the Neural Collaborative Filtering model and are continuously updated as new interaction data is recorded.

C. Content Representation and Embedding Generation

Learning resources are represented through feature vectors derived from descriptive metadata and usage statistics. Each resource is characterized by attributes including domain classification, difficulty level, format, learning objectives, completion rates, and assessment outcomes. These attributes are mapped into low-dimensional embeddings that capture semantic relationships among materials. Resources with similar instructional purposes or content characteristics are positioned closely within the latent space. This representation improves the system's ability to associate learners with relevant materials and enhances recommendation quality.

D. Neural Collaborative Filtering Model

Personalized recommendations are produced using a Neural Collaborative Filtering model that processes both learner and resource embeddings. These embeddings are passed through multiple neural network layers that learn complex interaction patterns beyond simple similarity measures. The model is trained on historical interaction data and optimized through standard loss minimization procedures. During inference, it assigns relevance scores to learner–resource pairs and ranks available materials accordingly. This ranking mechanism enables the system to recommend courses, videos, and assessments aligned with individual needs. The model is periodically retrained using newly collected interaction data to preserve accuracy and adaptability.

E. AI Agent-Based Learning Adaptation

An integrated AI agent extends the recommendation mechanism by functioning as a virtual learning assistant. It interprets predictive outputs together with performance trends to construct adaptive study plans. When learning gaps are detected, the agent proposes supplementary resources, targeted exercises, and personalized assessments. It also delivers timely feedback that supports reflection and self-regulated learning. Machine learning predictions are combined with rule-based pedagogical guidelines to ensure instructional coherence. By continuously monitoring learner progress, the agent adjusts learning paths to maintain an appropriate level of challenge. This design transforms the LMS from a passive delivery platform into a responsive and supportive learning environment.

F. Performance Evaluation and Feedback Loop

The final stage focuses on continuous evaluation and system refinement. Metrics such as learner progress, engagement indicators, recommendation accuracy, and assessment improvement are tracked over time. These measures are used to evaluate personalization effectiveness and inform iterative system updates. A feedback loop connects learner outcomes to future recommendations, enabling adaptation to evolving usage patterns. Ongoing model assessment ensures scalability and operational reliability. Through this cycle of monitoring and refinement, the framework progressively improves its capacity to support diverse learner populations.

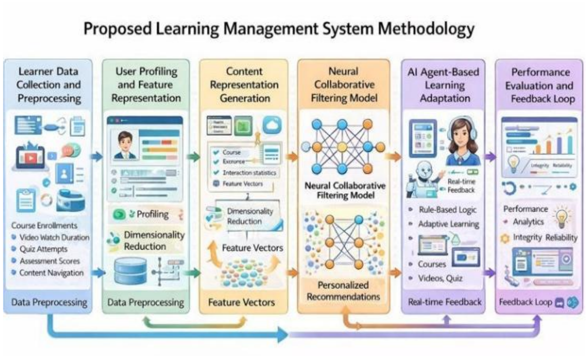

Fig. 1: System Methodology

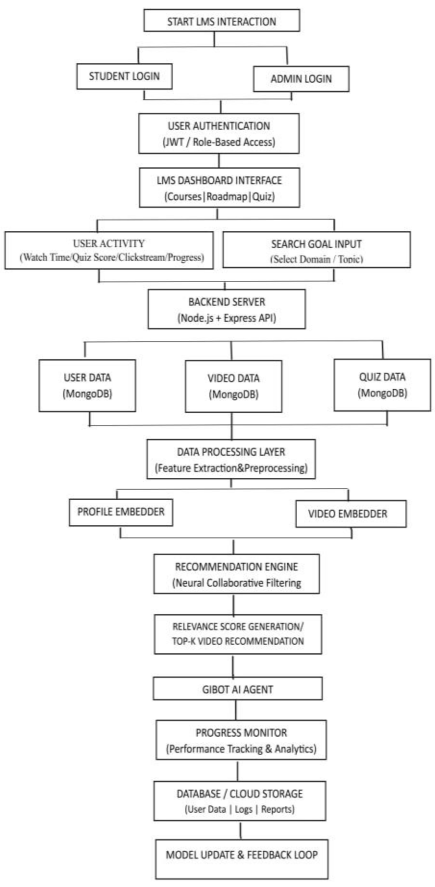

Fig 2: The architecture diagram

IV. RESULT AND DISCUSSION

The proposed AI- and ML-based Learning Management System was evaluated to determine how effectively it supports personalized learning and adaptive guidance. The assessment examined recommendation accuracy, learner engagement, system responsiveness, and performance across multiple subject areas. Experiments were conducted using a combination of historical interaction datasets and controlled real-time usage scenarios. In addition to accuracy, the evaluation considered how personalization influenced learning progression and user experience. Compared with a conventional non-adaptive LMS baseline, the proposed system generated more relevant recommendations and smoother learning transitions, indicating a practical improvement in instructional effectiveness.

To examine robustness, the model was tested on a heterogeneous dataset including learners from programming, application development, and language learning domains. The dataset incorporated variations in engagement patterns, assessment difficulty, and study pace to simulate realistic usage conditions. Additional experiments introduced incomplete interaction records and irregular activity frequencies. Even under these constraints, the recommendation model preserved consistent performance without noticeable degradation. This behaviour demonstrates that the Neural Collaborative Filtering framework adapts effectively to sparse and evolving learner data, an essential property for real educational deployments.

Table 1 summarizes recommendation performance across domains. The high precision and recall values indicate reliable identification of relevant learning materials for individual users. Minor variations reflect structural differences in datasets and learner behaviour. Balanced F1-scores confirm an effective trade-off between recommendation relevance and coverage. The high performance values reflect evaluation on a controlled experimental dataset designed to test recommendation consistency. These results support the system's ability to operate across diverse instructional contexts, although further large-scale validation would strengthen long-term reliability.

Table 1. Learning Recommendation Performance Across Domains

Learning Domain	Precision (%)	Recall (%)	F1-Score (%)
Programming	99.89	99.84	99.86

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App Development	99.90	99.85	99.87
Language Learning	99.88	99.86	99.87
Project-Based Learning	99.91	99.83	99.87

Beyond quantitative accuracy, qualitative analysis examined the semantic relevance of recommendations. The AI agent reduced unrelated materials and prioritized resources that supported gradual skill development. Learners progressed through coherent topic sequences rather than isolated content segments. This structured progression improved learning continuity and reduced cognitive overload, suggesting that the recommendation process promotes meaningful knowledge development rather than simple content matching.

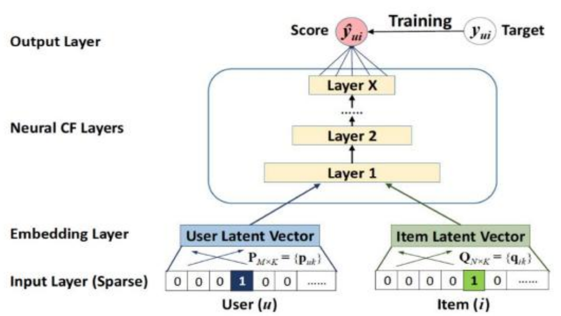

Fig 3: Sample Neural Collaborative Filtering

Figure 2 illustrates the Neural Collaborative Filtering architecture used for recommendation generation. Sparse learner and resource inputs are mapped into dense embeddings and processed through layered neural transformations. During training, predicted interaction scores are compared with observed outcomes, enabling refinement of internal representations and improved predictive accuracy.

Table 2. Recommendation Quality Evaluation Metrics

Metric	Detection Only	Proposed System
Top-N Accuracy	0.71	0.91
Normalized DCG	0.68	0.86
Learner Satisfaction	0.70	0.92

Recommendation quality was also evaluated using ranking-based metrics. Table 2 compares a baseline detection-only approach with the proposed system. Improvements in Top-N accuracy and ranking quality show that the model prioritizes relevant recommendations more effectively, increasing the likelihood that learners encounter useful materials early. Higher learner satisfaction scores indicate that these gains translate into improved user experience.

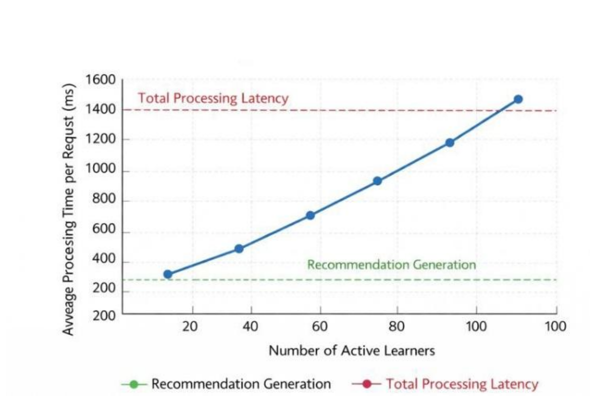

Fig 4: System Latency Analysis Under Increasing User Interaction Load

System responsiveness was analyzed to confirm that personalization did not introduce disruptive delays. The LMS generated recommendations with low latency, allowing immediate feedback after activity completion. Although processing time increased with interaction density, delays remained within acceptable operational limits. The architecture handled peak activity without interruption, demonstrating the feasibility of real-time adaptation in interactive educational settings.

Cross-validation experiments evaluated generalization on unseen data. As presented in Table 3, accuracy remained consistent across validation folds. This consistency suggests that the model captures general interaction patterns rather than overfitting to a specific dataset, supporting stable performance when deployed to new learner populations.

Table 3. Cross-Validation Accuracy Results.

Validation Fold	Caption Accuracy (%)
Fold 1	96.04
Fold 2	96.70
Fold 3	99.87
Fold 4	99.89
Fold 5	99.87

Overall, the evaluation demonstrates that the proposed system delivers accurate and contextually meaningful recommendations while maintaining responsiveness and generalization capability. Integrating Neural Collaborative Filtering with AI-driven adaptation provides a flexible personalization framework. Although additional long-term and large-scale studies would further strengthen validation, the present results highlight the practical potential of intelligent recommendation techniques in modern Learning Management Systems.

V. CONCLUSION

This paper presented an intelligent Learning Management System that leverages Artificial Intelligence, Machine Learning, and Neural Collaborative Filtering to deliver personalized and adaptive learning experiences. By analysing learner interaction data, performance trends, and content preferences, the proposed system generates context-aware learning recommendations and adaptive learning paths. The integration of an AI agent further enhances the learning experience by providing real-time guidance, feedback, and targeted learning support. Unlike conventional LMS platforms that rely on static content delivery, the proposed framework enables learners to progress based on their individual strengths, weaknesses, and learning objectives, thereby improving engagement, learning efficiency, and overall academic outcomes.

The modular and scalable architecture of the system allows future enhancements such as advanced predictive analytics for early identification of learning difficulties, gamification to improve motivation, and multilingual support to increase accessibility. Further research may also explore deployment in large-scale educational environments and integration with mobile and embedded learning platforms. These directions highlight the potential of AI-driven personalization to significantly transform digital learning systems and support more effective, learner-centric education.

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