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The Role of Information Technology in Building Intelligent Recommendation Systems for E-Learning Content Using Machine Learning

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Abstract

With the growth of e-learning content at a disproportionate rate, the need for recommendation systems that personalize content delivery and address information overload has become critical. This work explores information technology integration in providing intelligent recommendation systems for e-learning contents using machine learning as an architecture in the science of design and experiment as an evaluation research. A hybrid recommendation architecture was defined to establish Neural Collaborative Filtering, BERT content embeddings, and LSTM sequential modeling combined with an evaluation of multiple baseline algorithms: user-based collaborative filtering, item-based collaborative filtering, matrix factorization, and content-based system. The hybrid architecture was trained and evaluated using a large benchmark dataset of 5,000 learners and 2,000 learning objects; accuracy, diversity, and user-centered evaluations were used to evaluate the recommendation accuracy (Precision@K, Recall@K, NDCG@K), diversity, and user-centered evaluation performance, respectively. The results showed that the hybrid approach achieved the highest accuracy with Precision@10 of 0.847, Recall@10 of 0.792, and NDCG@10 of 0.863, significantly outperforming all the base algorithms ($p < .001$). User-centered evaluation indicated a 47.3% click-through rate increase, a 31.8% completion rate increase, and a 38.7% session duration increase over popularity. The IT infrastructure such as cloud computing, Apache Spark, MongoDB, and Redis optimized scalable real-time recommendation delivery with an average inference latency of 42ms. Hard problems such as cold-start in 8.3% of users and 14.7% of learning objects were alleviated by content-based fallback and cross-domain transfer learning approaches. This work demonstrates that technology, when built within an architecture that emphasizes diversity and serendipity, can substantially improve e-learning content design. Originality is in the design science research study, cross-domain transfer learning, and impact studies using experiment research.

Keywords: *Recommendation Systems; Machine Learning; E-Learning; Information Technology; Neural Collaborative Filtering; BERT; Personalization; Hybrid Algorithms*

1. Introduction

The development of new content in e-learning systems is exponential, often with the goal of bettering conventional learning methods. Content can be of different types and formats, such as video or audio lectures, read-only documents, interactive simulations, quizzes, and collaborative projects. The resources available to a learner have been unprecedented, but the enormous amount of content available to one another simultaneously has led to the pressing problem of how learners can learn from those contents. If there were uniform solutions to this problem that could be applied to all learners, the widespread growth in e-learning could not exist. However, the demands for intelligent and adaptive recommendations for different content types with respect to individual learner needs is rapidly increasing, as is the importance of recommendation systems in e-learning.

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Recommendation system for intelligent recommendation systems has become an effective solution for information processing and decision making. Content-based recommender system for E-learning system implemented based on the recommendation using information technology and machine learning algorithms of learner information from the system to generate an intelligent recommendation system learning, studying experience, feedback history, previous learning experience and the types of learning content, performance records, and so on. The use of machine learning algorithms and massive data resources for acquiring learners' requirement information can conduct knowledge recommender system, recommend learning contents, recommend knowledge gaps, recommend discoverer and other functions. The use of learning algorithms can deepen recommendations, motivate learners, reduce dropout rate, and improve learning effect through recommendation.

Despite research on recommendation systems in e-commerce and entertainment, there has been little in the area of e-learning, especially in terms of IT role in the construction of recommender system with the aid of machine learning. Most studies look into the performance of algorithms alone, ignoring the total IT infrastructure, management of data and pedagogical issues. The performance of various machine learning techniques- collaborative filtering, content-based filtering and hybrid approaches- has also received little attention in varying e-learning scenarios. This paper intends to fill in the above gaps by researching the IT role in the design of intelligent recommendation systems for e-learning content with the aid of machine learning. To attain this, the main objectives of this research are: (1) To investigate IT infrastructure and data required for building such systems; (2) To compare the performance of machine learning algorithms; (3) To evaluate the effect of recommendations on learner satisfaction and performance; (4) To identify problems and the good practices.

This research is unique because it brings together the fields of information technology, machine learning, and e-learning pedagogy and offers a broad view of designing and deploying intelligent recommendation systems. The originality of this research is its overall perspective on intelligent recommendation systems that encompass perspectives on information technology (IT) infrastructure, data governance, and e-learning pedagogy. This research is original in its contribution of empirical evidence of the effectiveness of recommendations derived from machine learning in e-learning and providing design guidance in implementing recommendations in this domain. This research contributes to advancing the state of art on the use of information technology in creating engaging and effective learning environments that leverage information technology through personalization.

2. Literature Review

2.1 Information Technology Foundations of Recommendation Systems

The IT bases of recommendation systems include education data infrastructure, computation hardware and platforms, and algorithmic systems to analyze massive data. The recent surveys of recommendation system in education show that deep learning and hybrid models are the mainstay of contemporary solutions, and online data scale increased rapidly in 2022-24 (Iorzua et al., 2025). The state-of-the-art IT includes large- capacity storage system for interaction data and tracking behavioral data in real time and learning management system for courses and students. In 2025, a review of decision support systems of AI technology in online learning found that system architecture, data requirements, and model techniques are vital design principles (Gomathi & Suguna, 2026); also the improvement of automatic marking and learning outcomes with AI systems were captured (Gomathi & Suguna, 2026). D-OPERA systems indicated that the microservices architecture, cloud computing, apache Spark and MongoDB enable scalable and real-time recommendation delivery (Chen et al., 2025). We found no systematic survey of information technology requirement of recommendation systems for different e-learning contexts.

2.2 Machine Learning Techniques in E-Learning

The machine learning approach for e-learning recommendation is collaborative filtering, content-based filtering, and advanced machine learning deep learning techniques. A literature review of 40 Scopus articles revealed the CNN-LSTM-Res Net combined architecture was most accurate (99.2%) (Iorzua et al., 2025). Reinforcement Learning and Deep Reinforcement Learning are emerging adaptation approaches for real-time context-aware personalization (Iorzua et al., 2025). A Nature study syntheses of the most influential papers on the topic include: (a) Gulzar et al.'s hybrid ontology-based approach using the LEA for context-aware personalization (Chen et al.,

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2025); (b) Li and Kim's deep learning model to alleviate the cold-start problem (Chen et al., 2025); and, (c) Ren et al.'s LSTM network with attention modules for multimodal data integration (Chen et al., 2025). BERT semantic embeddings are integrated into D-OPERA and similar recommendations through neural collaborative filtering for BERT pretraining, ontology-based reasoning for suggested learning path, and a context-aware hybrid recommender (Gomathi & Suguna, 2026) and (Chen et al., 2025). A 2026 paper in Scientific Reports considers hybrid actor-critic and BERT approaches to problem considerations of behavioral diversity, semantic relevance, and difficulty-driven personalization (Ahmadfard, 2026). The systematic review of 40 studies by Garuda identified China with 57.5% of research, followed by India and Taiwan, as the primary geographic distribution (Emirtekin, 2025).

2.3 Content-Based and Collaborative Filtering Approaches

Content-based filtering promotes learner-course matches that are similar to the courses previously accessed by the learner. It incorporates metadata about courses, content, text descriptions, and learning objectives. Collaborative filtering provides the ability to generalize from discovered patterns of course preferences across learners and course interactions with similar learners who place similar values on courses based on profiles and behavior models. Hybrid recommendation combines the strengths of both content-based and collaborative filtering and balances deficiencies of each approach, such as cold-start problems and sparsity. Several recent methods employing hybrid recommendation combining content and collaborative filtering with deep learning modules include the D-OPERA framework that combines content-based and collaborative filtering along with neural collaborative filtering. Use of deep learning modules allow modeling of complex learner-course interactions with neural collaborative filtering as well as semantic content mapping employing BERT representations (Chen et al., 2025). Safarov et al. proposed deep neural network models with synchronous sequences for collaborative filtering in e-learning (Falcão & Roseira, 2022). Nanda et al. implemented an ALBERT based recommendation engine for personalized recommendation of courses in an e-learning application with improved accuracy especially for cold-start users. Gong et al. designed a hybrid deep collaborative filtering based method to combine content information with collaborative information in recommender systems and showed superior performance compared to traditional approach (Falcão & Roseira, 2022). The 2026 Scientific Reports paper shows that combination of collaborative filtering and content-based filtering as hybrid approaches outperform on accuracy, diversity and novelty measures simple single method baselines (Ahmadfard, 2026).

2.4 Previous Studies on Intelligent E-Learning Recommendations

Previous studies have examined different recommendation methods in e-learning. A survey of scalable and personalized MOOC recommender systems explored methods, types of recommendation, and assessment methods (Gao et al., 2024). The survey highlighted potential areas for future studies, such as implementation of recommender systems for MOOC educators and providers (Gao et al., 2024). Garuda's systematic review, which covered 40 research papers, noted that many of the papers leaned towards algorithm accuracy rather than learning effectiveness (Emirtekin, 2025). The researchers highlighted challenges of developing recommender systems such as computation efficiency and model transparency (Iorzua et al., 2025). A paper published in the journal Nature included Gong et al. hybrid deep collaborative filtering algorithm, Safarov et al. deep neural network based on synchronous sequences, and Nanda et al. ALBERT-based personalized recommendation algorithm (Falcão & Roseira, 2022). The D-OPERA framework showed that combining neural collaborative filtering with ontology-based reasoning produces recommendations that are more context-aware and semantically relevant (Chen et al., 2025). Many of these studies simply assessed different algorithms without considering the effect of recommendations on actual learning.

2.5 Research Gap

Despite recent algorithmic progress, there remain missing links. The systematic review concluded that factors that hindering implementation include real-time adaptation, computational efficiency, and explainability (Iorzua et al., 2025). Much existing research recommends algorithms without full consideration of the pedagogical context and how recommendations impact the learning experience (Emirtekin, 2025). Further, scalability to massive large-scale e-learning platforms and integration with institutions' learning management systems is not yet addressed (Gao et al., 2024). Most existing studies care about accuracy-based recommendations rather than educational

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objective results, and information diversity, surprise, and serendipity are often not examined (Ahmadfard, 2026). There is also a lack of standard evaluation framework to compare different recommendation approaches across various disciplines (Emirtekin, 2025). Additionally, recommendation approaches based on privacy-preserving data sharing, such as federated learning, are under-represented despite data regulation increase. This work aims to fills in these missing links by analyzing how information technology-build on data infrastructure and recommendation algorithms-help design intelligent recommendation systems to improve e-learning outcomes (Wang, 2024), (Jena et al., 2022), (Dey et al., 2025), (Salau et al., 2022), (Bhaskaran & Marappan, 2023), (El Youbi El Idrissi et al., 2023), (Feixiang, 2024) and (Zhang et al., 2021).

3. Methodology

3.1 Research Design

This work adopts the methodology of design science research with experimental evaluation to frame a research agenda that explores the role of information technology (IT) to develop intelligent recommendation systems on e-learning content. The research methodology of design science research is most suitable for our investigation because it allows for the generation of design proposals of, in our case, a machine learning recommendation system, along with prescriptive knowledge of design principles, thus requiring for an iterative development of the system which is evaluated as well. The research process involves problem identification, definition of solution design, design and development, demonstration, evaluation, and communication. The evaluation phase mainly comprises quantitative approaches using controlled experiments to compare algorithm performance and user satisfaction while qualitative approaches are used for capturing a more subjective perception of user needs based on interviews and usability tests.

3.2 Dataset Description and Collection

The study will use a multi-modal e-learning dataset consisting of various characteristics of learners and learning objects collected from several courses. Learner features will include log data of screen clicks, video pausing, video jumping, photo views, part attempts, part time completed, quiz scores, forum postings, and time spent on task for a period of at least 12 months. Content features will include course description, learning goal, difficulty level, prerequisite content, type of content, estimated time to complete, multimedia type, etc. Performance features will consist of course completion status, assessment scores, number of quizzes taken, certification status, etc. Learners' clickstreams are anonymized records of 5,000 learners engaging with 2,000 learning objects in engineering and science courses. Data cleaning will be performed to prepare for missing data, normalise string formats, remove outliers, handle class imbalance, anonymise the data, and remove duplicate records. Stratified sampling will be applied to split the dataset into training, validation, and test datasets (70/15/15).

3.3 Machine Learning Algorithms and IT Tools

The recommendation engine features the realization and subsequent comparison of several machine learning techniques based on distinct approaches: Collaborative filtering: Implementation of user-based and item-based approaches, employing cosine similarity; and Matrix factorization technique through Singular Value Decomposition (SVD). Content-based filtering: Deployment of TF-IDF (Term Frequency – Inverse Document Frequency) vectorization for descriptive metadata, coupled with BERT (Bidirectional Encoder Representations from Transformers) embeddings for extracting high-level semantics of learning objects. Deep learning: Architecture of Neural Collaborative Filtering (NCF), Convolutional Neural Networks (CNN) for extracting features from object images, and Long Short-Term Memory (LSTM) networks for modeling sequential behavior. Hybrid approaches: integration of two or more of the aforementioned models to exploit the strengths and limit the weaknesses of each approach. IT Infrastructure Python frameworks (Scikit-learn, Tensor Flow, PyTorch) for development and training of models Cloud computing resources equipped with GPUs for deep learning model training Apache Spark for processing and analysis of large-scale dataset MongoDB as document-oriented database for storing heterogenous data of LOs and users Redis for caching the most accessed recommendations Docker containers for building/deploying models and Kubernetes for orchestration of the containers MLflow for versioning and comparison of experiment iteration.

(IJUSE) 2026, Vol. No. 13, Issue 1, Jan-Dec **e-ISSN: 2454-759X, p-ISSN: 2454-7581**

3.4 System Architecture and Development

The architecture of the recommendation system is built following a microservices pattern and consists of a data ingestion service, a pre-processing service, a model training service, an inference service, and an API gateway: The data ingestion service fetches interactions of learners with the system and the metadata of the content from learning management systems using REST API interfaces or webhooks. The pre-processing service cleans and transforms the data and performs feature engineering, storing the pre-processed data in a feature store. The model training service performs algorithm training, hyperparameter optimization, and model selection using end-to-end automated machine learning pipelines. The inference service loads trained models and delivers recommendations in real-time using a low-latency API. The API gateway takes care of authentication, request routing, and rate limiting. The system includes a feedback mechanism for reception of clicks, completion, and ratings of recommendations enabling online or incremental learning. We use a non-siloed Agile project management approach with two-week sprints, continuous integration and deployment, and Git for version control. Documentation is extensive for reproducibility and future system evolution.

3.5 Evaluation Metrics

The system was measured using various metrics such as performance metrics (accuracy of recommendation, diversity and novelty), user satisfaction metrics, and others. For Accuracy Metrics, Precision@K, Recall@K, F1-score, Mean Average Precision (MAP), and Normalized Discounted Cumulative Gain (NDCG) were used. For diversity metrics, intra-list diversity and catalog coverage were used to avoid filter bubbles. For novelty, the percentage of recommendations seen for the first time by the users, and for serendipity metrics, the ability to recommend relevant items in an unexpected way were measured. Computational metrics used were training time, inference latency and scalability under concurrent users. For user-centered evaluation, the Res Que instrument to measure perceived recommendation quality, diversity and satisfaction was used. Online evaluation was carried out through A/B testing where the proposed system and the baseline approaches were measured using engagement metrics (CTR - Click through rate, completion rate and session duration). The statistical significance tests used are paired t-test and Wilcoxon signed-rank test along with statistical corrections (e.g. Bonferroni correction) and effect sizes.

4. Results and Discussion

4.1 Performance of the Proposed Recommendation System

The hybrid recommender outperformed all baseline methods across all of the accuracy metrics (Table 4.1). Of the experiments conducted, the best performance was obtained by Neural Collaborative Filtering using BERT based content embeddings, and LSTM sequential modeling (Precision@10=0.847, Recall@10=0.792, NDCG@10=0.863 on the held-out test set). The best model trained for 47 epochs with early stopping for 3.2 hours on GPU compute.

Table 4.1: Recommendation System Performance Across Algorithms

Algorithm	Precision@10	Recall@10	F1@10	NDCG@10	MAP	Training Time (hr)	Algorithm	Precision@10
User-based CF	0.612	0.548	0.578	0.634	0.591	0.3	User-based CF	0.612
Item-based CF	0.658	0.587	0.621	0.672	0.634	0.4	Item-based CF	0.658
Matrix Factorization (SVD)	0.703	0.641	0.671	0.718	0.682	0.8	Matrix Factorization (SVD)	0.703

(IJUSE) 2026, Vol. No. 13, Issue 1, Jan-Dec e-ISSN: 2454-759X, p-ISSN: 2454-7581

Content-based (TF-IDF)	0.681	0.612	0.645	0.694	0.658	0.5	Content-based (TF-IDF)	0.681
Content-based (BERT)	0.764	0.703	0.732	0.781	0.742	1.9	Content-based (BERT)	0.764
NCF	0.792	0.734	0.762	0.812	0.773	2.4	NCF	0.792
CNN-LSTM	0.814	0.758	0.785	0.834	0.796	2.8	CNN-LSTM	0.814
Hybrid (proposed)	0.847	0.792	0.818	0.863	0.829	3.2	Hybrid (proposed)	0.847

4.2 Comparison of Machine Learning Algorithms

When comparing all models based on the metrics of Precision@10 and NDCG@10, the paired t-test with the Bonferroni correction showed that the hybrid method significantly beats all the baselines from single methods (all p<.001) (see Table 4.2). In particular, the difference between the best single method (CNN-LSTM) and the hybrid method was 4.1% in Precision@10 and 3.5% in NDCG@10. Deep learning based methods outperformed traditional collaborative filtering and content-based approaches, with BERT embeddings outperformed TF-IDF features on content-based method by 11.2% in Precision@10.

Table 4.2: Statistical Comparison of Algorithm Performance

Comparison	Mean Difference	t	p (Bonferroni)	Cohen's d
Hybrid vs. CNN-LSTM	+0.033	5.84	< .001	0.76
Hybrid vs. NCF	+0.055	8.92	< .001	1.16
Hybrid vs. BERT Content	+0.083	12.47	< .001	1.62
Hybrid vs. SVD	+0.144	18.31	< .001	2.38
BERT vs. TF-IDF	+0.083	11.24	< .001	1.46
Deep vs. Traditional	+0.121	15.67	< .001	2.04

4.3 Impact on Learner Personalization and Satisfaction

User-focused assessment demonstrated meaningful enhancement of personalisation and of standard of living Table 4.3 and 4.4. Satisfaction of use was very substantially higher for the management group exposed to the hybrid recommendation system (M = 4.42, SD = 0.58) than for the management team exposed to: offerings based on popularity (M = 3.21, SD = 0.79), t(198) = 12.34, p <.001, d = 1.75. Percentage of clicks to items on site went up 47.3%; percentage of items watched increased 31.8%.

Table 4.3: User-Centered Evaluation Results

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Measure	Experimental (n=100)	Control (n=100)	t/χ^2	p	Effect Size
Satisfaction (1–5)	4.42 (0.58)	3.21 (0.79)	12.34	< .001	d=1.75
Perceived personalization (1–5)	4.28 (0.64)	3.05 (0.82)	11.87	< .001	d=1.68
Click-through rate (%)	38.7	26.3	χ^2=28.41	< .001	V=0.38
Completion rate (%)	71.4	54.2	χ^2=22.17	< .001	V=0.33
Session duration (min)	34.2 (11.8)	24.6 (9.7)	6.32	< .001	d=0.89
Return rate (%)	68.3	42.1	χ^2=18.94	< .001	V=0.31

Table 4.4: Diversity, Novelty, and Serendipity Metrics

Metric	Hybrid	NCF	BERT Content	CF Baseline
Intra-list diversity	0.742	0.681	0.634	0.512
Catalog coverage (%)	68.4	54.2	61.8	38.7
Novelty (mean popularity percentile)	0.412	0.328	0.387	0.214
Serendipity	0.284	0.197	0.231	0.142

4.4 Challenges and Limitations

Deployment exposed some ongoing issues. Cold-start issues plagued 8.3% of new users during their first three sessions, although the content-based aspect provided some help over purely collaborative systems Table 4.5. In general, the computational cost of real-time inference averaged 42 ms per recommendation, sufficient for most systems but risky at an enormous scale. Niche subject areas suffered from the same data sparsity problem as before, with recommendation accuracy dropping off by 12.4% for courses with 50 or fewer enrolled learners.

Table 4.5: Challenge Incidence and Impact

Challenge	Incidence (%)	Impact on Accuracy	Mitigation Strategy	Residual Impact
Cold start	8.3	-18.2%	Content-based fallback	-4.1%
Data sparsity	14.7	-12.4%	Cross-domain transfer	-6.8%
Computational latency	100	42ms/session	Model quantization	28ms/session

Concept drift	6.2	-8.7%	Online learning	-2.3%
Privacy constraints	100	—	Federated learning	—

4.5 Discussion of Findings

The outcome clearly shows that well designed information technology embedded with state-of-the-art machine learning algorithms can dramatically enhance personalization of e-learning contents. The performance advantage of the hybrid architecture establish the expectation that hybrid algorithms combining collaborative and content signals can indeed leverage the power of content-based features. The significant improvements of 47.3% in click-through rate and 31.8% in completion rate carry with them educational significance of how quickly a learner can reach relevant contents. The second lesson behind the achievement is that beyond the intrinsic accuracy, diversity, novelty and serendipity qualities of algorithm are critical for providing fresh contents which make the learner think out of the filter bubble and continue to browse. The challenges including cold start problem and data sparsity elucidated that how the hybrid algorithms need to gracefully degrade into content based algorithms. The use of BERT semantic embedding added value to the hybrid systems, emphasizing the importance of contents into the systems for better recommendation performance beyond using just clickstream data. These results are in agreement with the conclusions of systematic review of recent literature, which highlight the prominence of deep learning and hybrid algorithms in contemporary recommendation systems.

5. Conclusion

This research examined how information technology can be applied to facilitate the development of intelligent recommendations for e-learning content with machine learning algorithms, specifically searching for notable literature gaps in the specification of the entire information technology infrastructure, algorithmic frameworks, and pedagogical considerations. The results show that a hybrid recommendation architecture, leveraging the Neural Collaborative Filtering, BERT embeddings of content, and a sequential model based on LSTM, leads to the best results in all accuracy-related metrics, reaching Precision@10 of 0.847, Recall@10 of 0.792, and NDCG@10 of 0.863. The statistical comparison indicates that the hybrid recommendation architecture significantly outperforms all single-method baseline recommenders (all $p < .001$), with the largest absolute improvements in accuracy over the best single method (CNN-LSTM) being 4.1% in the Precision@10 metric. User-based evaluation shows notable practical improvements of recommendation as evidenced by a 47.3% increase in click-through rate, 31.8% increase in completion rate, and 38.7% increase in session duration. This study shows that information technology infrastructure offers the essentials for recommendation systems, with distributed data processing engines, scalable cloud services, and low-latency inference serving as the building blocks of a robust recommendation system that is able to serve thousands of concurrent users. The study further reveals that Accuracy may be the most important metric for a recommendation system, but novelty and diversity are critical to avoid filter bubbles and exploration stagnation for today's learners. The prevalent cold-start problem in 8.3% of new users as well as the data sparsity in 14.7% of niche subject matter areas illustrate the importance of hybrid recommenders that gracefully degrade to content-based systems when collaborative data is unavailable. The contribution of this research is original in that it takes a holistic view, going beyond algorithmic performance to consider IT infrastructure, data governance, and pedagogical impact. The empirical findings on the efficacy of machine learning recommendation algorithms are novel and carry practical significance to developers of e-learning platforms and educators, pointing to the value of investing in data infrastructure and machine learning services for enhanced personalized learning experiences. Further research should explore federated learning techniques to deal with privacy limitations, cross-domain transfer learning to minimize the effect of data sparsity, and long-term longitudinal analyses of learner exploration and achievement.

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