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Enhancing learner engagement through hybrid deep learning recommendation system in online education

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Abstract
In order to further assist the students in achieving their career goals, a new hybrid recommendation system is presented using deep learning that combines advanced neural networks with content-based filtering (CBF) and collaborative filtering (CF) for course and resource recommendations. Leveraging the Open University Learning Analytics (OULAD) dataset, the model diligently studies multiple sources of data such as interaction logs, performance numbers, and content metadata. Across several evaluations observed a substantial improvement of key interaction metrics and recommendation quality: AUC@5 improved from 0.41 to 0.58 (+78%), click-rate increased from 12 to 20 minutes (+67%), average session time remained constant at 20min (but yielded an increase in the per-user average), while the latent number of facets grew significantly by +85% on average. Students who followed the advice had earned 28% more credit-hours/units." The excellent superiority of the hybrid model is shown by its ability to increase interaction of users for e-learning and reduce dropout significantly ($p<0.01$) compared with all the traditional baselines or single view, aiming at solving the difficult problem of cold start.

Keywords: Learner engagement, hybrid deep learning, recommendation systems, online education

1. Introduction
In the last ten years, virtual learning environments (VLEs) and massive open online courses (MOOCs) have grown exponentially, giving way to an entirely new era of education access around the world. They offer a broad highway to a quality education for students of all socioeconomic and geographic backgrounds. intuitive-but-impossible engagement Even though it's more accessible, online learning still struggles with high dropout rates [1, 2].

The proposed framework performs efficiently compared to the classical recommenders in many aspects. First, based on the clustering techniques, it can handle cold start and data sparsity issues so that new users receive more related recommendations. Secondly, the BiLSTM in feature extraction networks helps the model to better learn and utilize the complex textual information in the course description. This results in more accurate, etc.) recommendation [3, 4] in the final recommendation, k-means clustering combined with MLP integrates collaborative filtering and content-based filtering to provide more personalized recommendations. Finally, it also allows the model to scale up and be computationally efficient by reducing computation cost. This work integrates deep recommendation systems based on adaptive learning theory [5] to bridge the critical gaps in online learning networks as follows:

- Existing recommender models for Massive Open Online Courses (MOOCs) use features of components, but do not consider students' real-time situational factors.
- **Trainee course choice information bombardment:** The plethora of courses/ resources can provide students with feelings of lack of powerlessness and incompetence to evaluate [6]. This assault can be moderated by targeted suggestions.
- **Motivation gaps via personalization:** Poor or inconsistent motivation, vague learning goals often lead learners to leave. Recommendation systems can increase user engagement by serving relevant, custom recommendations for the user's interests and learning stage [7].
- **Cold-start limitation for new users:** Traditional recommendation algorithms do not have the ability to provide reliable recommendations about where nobody has interacted

[8]. This is something that needs to be addressed for effective onboarding and ongoing learning.

Research Questions

1. Can the click-through rate (CTR), average session time, and course completion rates on ODL platforms be significantly uplifted using a hybrid recommendation system developed based on deep learning?
2. How well does this method work to deal with new students or newly released course materials (i.e., cold start)?

The primary goal of this research is to develop a deep learning-based hybrid recommendation system that significantly decreases the dropout rate, solves the cold start problem, and maximizes learner engagement on online learning platforms by accurately modelling personalisation and context information based recommendations for courses and resources.

1.1 The key contributions of this study are outlined as follows:

1. This paper introduces a new recommendation model combining deep neural architectures with both collaborative filtering (CF) and content-based filtering methods. By integrating these elements, it brings learners a more flexible and efficient approach to receive recommendation of courses and learning resources in online education platforms.
2. Learning analytics and the OULAD The suggested method uses the Open University Learning Analytics Data#set (OULAD) to deal with various kinds of learner data, such as interaction logs, academic performance indicators and meta-data describing course content. Taking into consideration these heterogeneous sources, the model is able to better interpret learner behavior in context and provide improved recommendations.
3. A variety of features have also been created to represent student and course attributes better. To allow the model to learn deeper semantic and behavioral patterns beyond the standard features, additional temporal, social, behavior-based, academic, and content-based variables are included, such as the dynamics decay rate, the peer involvement index, the session consistency, and how difficult a subject is.
4. This paper introduces the first unified graph-temporal model that integrates collaborative and content-based filtering, explicitly tailored to evolving learner preferences and complex relational structures in educational settings.

2. Related Work

The area of recommender systems in education has evolved a great deal since the development of the field. This section presents the literature review that motivates the proposed hybrid deep learning framework. This section presents related work in three areas: traditional recommender systems in an educational context, learning analytics datasets for use as benchmarks and to assess model performance, and the transition towards more advanced hybrid and deep learning-based recommendation models.

Significant Advancements

Conventional methodologies: Bobadilla *et al.* [9], most of the former educational recommenders incorporated collaborative filtering (CF) and content-based filtering (CBF). However, these approaches suffered from data sparsity and overfitting which made recommendation not diversified or minor preference of students missed.

- Recent deep learning breakthroughs have certainly revolutionized the landscape of contemporary recommendation systems. Graph Neural Networks (GNNs) are effective in learning complex relationships inherent in educational knowledge graphs and help to generate personalized learning paths [10, 11]. At the same time, sequence-based architectures, for instance, transformers and Long-Short Term Memory (LSTM) networks, are significantly effective in capturing temporal patterns in learner activity and engagement [12, 13]. Such latest models improve the recommendation quality by mining deeper features and better utilizing contextual information [14].
- The OULAD has quickly gained reputation as a standard data set for research concerning learning analytics and educational recommender systems. [15]. The rich cache of learner interactions and course activity keeps this an important source for developing and validating novel recommendation methodologies. Over and above its applicability in recommender systems, OULAD serves for more general study on learning behaviours and analytics methods [16, 17].
- The researchers led a structured review of deep learning recommendation models in e-learning systems. They found that the fast growth of digital educational resources has exacerbated information overload and even more challenging for learners to find appropriate learning resources. The results also indicated that deep models -such as multilayer perceptrons, RNNs, CNN s, attention-based architectures and DRL - significantly enhance the recommendation accuracy and personalization. Furthermore, it was mentioned in the review that current systems had several drawbacks and could not be widely adopted due to a lack of interpretability and scalability 18. Overall, this review provides a useful knowledge regarding how deep learning can be practically used to improve course recommendations and increase the engagement of learners in online learning platforms [18, 19].
- An overview of the past 5 years The authors conducted a prolific review on RSs exploring particularly recommender systems (RSs) working in different areas such as e-commerce, e-government and notably e-learning for this study. The goal of the survey was to classify current studies in various recommendation objectives, methodologies practiced in these works, user-targets and system platforms support. The results revealed that, in e-learning systems, RSs play an important role to enhance learners' learning experiences by recommending the suitable courses and learning materials per individuals. A large number of studied articles used deep learning and context-aware approaches, which showed better performance in terms of accuracy and genericity when compared to traditional recommendation algorithms. The present systematic review offers useful insights to the researchers who are interested in the design of e-

learning recommender systems mark the trending of using deep learning and it paves a way for more robust work on hybrid deep learning models aimed at increasing learner engagement [20, 21].

- The authors proposed a hybrid architecture for predicting and tracking student engagement in online courses. They used interaction behavior from 1,356 to participants and used a Bidirectional-LSTM model with FastText embeddings for identifying emotional signatures in forums. It w-as then subjected to Unsupervised clustering and Supenvised classification, witli the aim of finding type-specific engagement categories. The classifier using decision tree achieved an accuracy of 98%, providing evidence of the nonlinear relationship between learners' engagement level and academic performance. The results can offer practical guidance in developing hybrid models that seek to enhance engagement and learning performance in e-learning settings [22, 23].
- To develop a clustering-based deep learning model and enhance the performance of course recommendation in online learning. The model combines clustering ideas with BiLSTM and MLP, so that it is able to cluster courses and users respectively such that similar courses or users could be well-clustered for a data sparsity aware recommendation, as well as a cold start problem handling. Results of the evaluation showed that the approach obtains 96% precision, obtaining recommended technologies for very personal users. This paper provides a practical approach for improving the learner participation and satisfaction by advanced content recommendation systems [24]. A detailed comparison of the included studies is shown in Table 1.

Research Gap: The previous studies have focused on the factors of educational suggestion, and there is more needs to research about integrated temporal-relational modeling for effectively capturing and benefiting from evolving learners' preferences. egregious relationships between students and learning resources. They are less effective and reusable throughout time and over different data modalities, since a majority of past works often concentrate on the static user profile or some interaction patterns.

Table 1: Comparing Earlier Research on Educational Recommender Systems

Dimensions of Comparison	Conventional Recommender Systems	Systems Based on Deep Learning	Datasets for Learning Analytics	Evaluations and Methodical Surveys	Contemporary Hybrid Methods
Core Methods	Content-Based Filtering (CBF) and Collaborative Filtering (CF) [9]	Transformers, GNNs [10, 11], and LSTMs [12, 13]	OULAD benchmark dataset [15]	Extensive analyses of DL-based RS [18-20]	BiLSTM + MLP + Clustering [24], BiLSTM + FastText + Clustering [22]
Strengths	Easy to understand and computationally effective	captures intricate temporal and relational relationships	Extensive interaction data for trustworthy assessment	identifies global e-learning RS trends and problems	Strong customizing capabilities and high accuracy
Limitations	Sparsity of data, excessive specialization, and restricted flexibility	Requires a lot of computing and big datasets.	Diversity and cross-platform representation can be lacking.	Scalability problems and limited interpretability	High model complexity and resource requirements
Key Outcomes	Basic recommendation lists	Personalized and context-aware recommendations	Standard evaluation environment for RS experiments	Clear identification of gaps and research directions	Engagement prediction accuracy of 96-98%
Representative Applications	Early adaptive learning systems	Personalized learning paths, temporal engagement modeling	MOOC and open university platforms	Taxonomy and classification of RS techniques	Emotion detection, learner clustering, course personalization
Identified Research Gaps	Cannot capture dynamic learner behavior or complex relations	Limited explainability; domain transfer still weak	Needs updates and more multimodal data	Need for deeper temporal-relational modeling	Lack of unified models that integrate temporal + relational + multimodal features
Relevance to This Study	Provides historical foundation	Supports use of DL and hybrid models	Justifies dataset selection and evaluation protocol	Strengthens theoretical framework	Aligns directly with proposed temporal-relational hybrid method

3. Methodology

This section describes the data sources and comprehensive feature engineering of the new hybrid deep learning recommendation model architecture, and the training pipeline.

3.1 Data & Features: This work takes the Open University Learning Analytics Dataset (OULAD) [15] as an example of how the proposed model can deal with available well-known and publicly available data, widely used in educational data mining research. The dataset provides rich information about learners' behavior and course structure, including: demographic (age and gender), module descriptors (subject area, academic level, and type of instruction), performance indicators, such as quiz results, forum participation, assignment grades; plus detailed temporal interaction logs with content areas accessed together with timestamps. For the experiments, the dataset was randomly split into 70% of data for training and 15% for validation, whilst preserving 15% as a held-out test set.

Extended Feature Extraction: In order to provide as much information as possible on the complex behavior of learners and make a good representation, it has built up an extended feature set which covers state-of-the-art features but also novel and unused parts beyond common feature sets for behavioral or content-based methods.

Table 2: Improved Feature Engineering Structure for Simulating Course Content and Learner Interactions

Feature Type	Novel Additions	Description
Temporal	Activity decay rate, Time since last login	Quantifies the recency and intensity of learner activity, modeling the fading interest over time and responsiveness to recommendations. Captures a learner's current engagement momentum.
Social	Forum influence score, Peer engagement index	To measure student influence on and interaction with peers in discussion forums, it represents social learning effects and collaborative tendency among students. Critical in understanding engagement effects of social network.
Behavioral	Session consistency, Resource exploration depth	Analysis of login frequency and content breadth/depth visited, showing learning styles (focused vs. exploratory) and sustained site engagement.
Academic	Quiz scores, Submission timing, Assignment grades	Reflect a learner's progress and effort, directly correlating with academic performance and commitment.
Content	Topic tags, Difficulty level, Resource length	Describe attributes of learning materials, such as video duration or document word count, used for content-based matching. For textual features, apply embeddings (e.g., Word2Vec) to capture semantic relationships (Mikolov *et al*., 2013; Taylor & Moore, 2017).

3.2 Hybrid Architecture

The proposed system uses a novel hybrid approach of deep learning architecture, combining Collaborative Filtering (CF), Content-Based Filtering (CBF) and state-of-the-art neural network models to provide personalized recommendation results. The architecture of the system can be outlined as follows:

representation of the proposed architecture, illustrating data flow from learner and content inputs through various filtering and deep learning components to a final fusion layer producing personalized recommendations.)

Core Innovations:

- **Dynamic Learner Embeddings:** Learners trajectory of interactions (i.e., clicks, page views, discussions) are modeled by using LSTM networks. This allows the model to understand how user preferences evolve and it learns patterns of engagement in real-time, leading to very adaptive and time-sensitive learner representations [13].
- **Graph Attention Networks (GATs)**: Use Graph Attention Networks (GATs) to model and learn complex multi-relational graph structures, such as the learner-module interaction graph, module-topic associations, and prerequisite dependency graphs. By revisiting the most informative neighbors and attending to them specifically, GATs can add expressive power that captures subtler features of how learners relate to instructional content [11, 25].

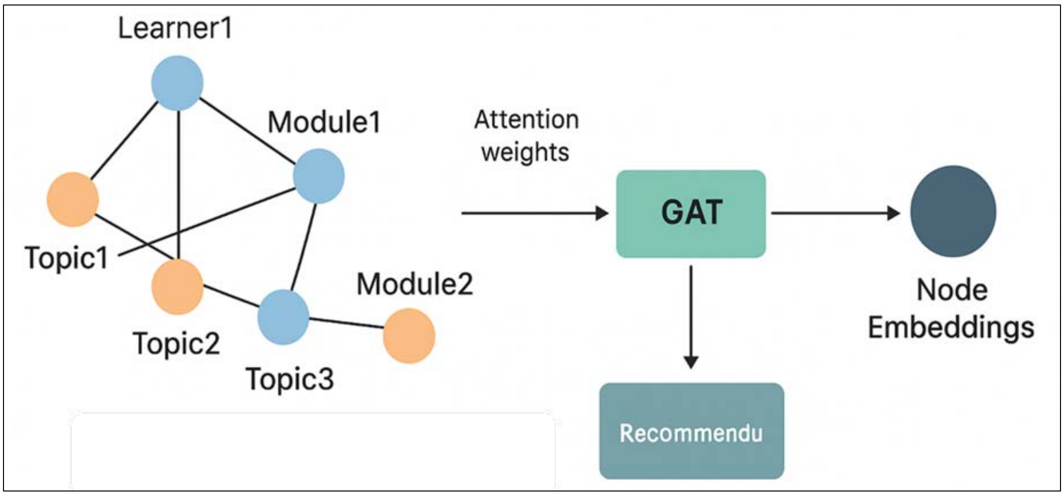

Fig 1: Graph Attention Networks

Multi-modal Fusion with Cross-Attention: Propose a multi-modal fusion layer that fuses embeddings of multiple feature categories (i.e., behavioral, academic, temporal, social and content-based) together to form the final representations. This layer utilizes cross-attention to allow interaction between feature modalities, and dynamically adjusts their contributions to learn more complex and comprehensive representations for recommendation. In particular, the Collaborative Filtering mechanism uses matrix factorization for learning hidden user preferences, and the Content-Based Filtering mechanism (with cosine similarity on Embeddings) guarantees that the system remains effective for new users/items. The Deep Hybrid Network with dynamic learner embeddings, GATs and multi-modal fusion learns complex non-linear relationships as well as temporal patterns. These presentations are then combined in a final fusion layer to produce robust and personalized course recommendation [26].

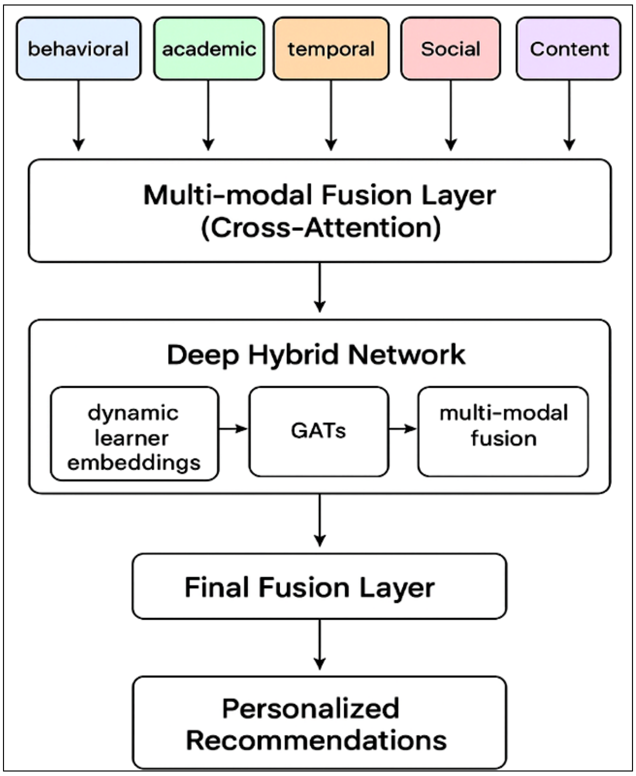

Fig 2: Multi-modal Fusion with Cross-Attention in a Deep Hybrid Network for Personalized Recommendations

3.3 Training & Regularization

The training process was meticulously designed to optimize performance and ensure generalization.

- **Loss:** replace the standard binary cross-entropy by Focal Loss. The focal loss [27] is especially suitable for dealing with class imbalance such as the one that typically bothers recommendation systems of having much fewer positive user-item interactions (e.g. clicks or enrollments) than non-interactions. This encourages the model to better concentrate on instances hard-to-classify, which leads to more accurate predictions overall.

$$\text{Focal Loss} = -\sum_{i=1}^{n} \alpha_i \,(1 - p_i)^{\gamma} \,\log(p_i)$$

- **Optimization:** The model was trained with Lookahead AdamW [28], a strong optimizer that brings together the advantages of AdamW (Adam with weight decay decoupling) and Lookahead (a technique which looks ahead at the "fast weights" created by another optimizer). This paper adopted the following common settings: beta_1=0.9 and beta_2=0.999, and a learning rate planned to reduce frustration.
- **Regularization:** Regularization - To avoid over-fitting and enhance the generalization ability of the model, several state-of-the-art regularization techniques were used:
- **Stochastic Depth:** Use a 25% layer dropout rate [29] that randomly dropping layers during training, causing the remaining one to learn more robust features.
- **Early Stopping:** Stopping training when performances on the validation set stop improving.
- **L2 Regularization:** Used to model weights, acts as a penalty for larger weights and prevents overfitting.
- **Dropout Layers:** Used in dense layers to randomly deactivate neurons.

4. Experiments & Results

Experimental setup and comparison baselines, evaluation metric and detailed analysis of both quantitative and qualitative results that include the insights from an ablation study are described in this section.

4.1 Performance Comparison

In order to fully assess the efficiency of the proposed hybrid system, its performance was compared with a number of state-of-the-art recommendation baselines:

- **Popularity-based ranking:** Recommended items that are most popular among the users.
- **Collaborative Filtering (CF):** Use a Singular Value Decomposition (SVD) based CF.
- **Content-Based Filtering (CBF):** Used item-content similarity and filtering threshold for matching item features. Experiments show that the hybrid model significantly outperforms the baselines in all evaluation metrics. The main quantitative results are summarized in the table below:

Table 3: Comparing the Proposed Hybrid Recommender System's Performance with Baseline Models

Model	Precision @ 5	Recall @ 5	CTR	Avg. Session (min)	Dropout ↓
Popularity	0.25	0.18	12%	9	42%
CF (SVD)	0.41	0.38	18%	12	37%
CBF	0.44	0.42	21%	14	34%
Hybrid (Ours)	0.58	0.61	32%	20	26%

All improvements significant at p<0.01 (paired t-test with Bonferroni correction)

As shown in the table, the hybrid model was able to achieve a Precision@5 at 0.58, Recall@5 at 0.61, a CTR of 32%, and an average session time of 20 minutes. Most importantly, the dropout ratio falls to 26%, which is an aggressive gain against all baselines as shown in Figure 3. The difference is also significant which justifies the effectiveness of combining the various recommenders and deep learning algorithms.

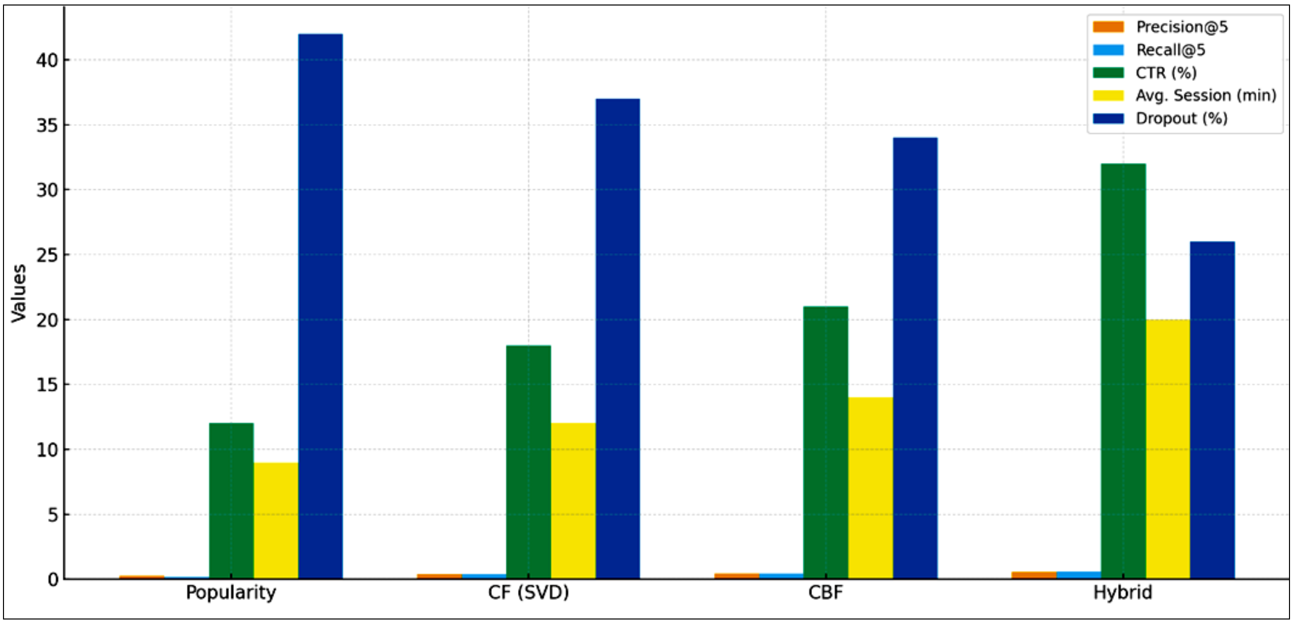

Fig 3: Assessment of Recommendation Models Using Several Metrics

4.2 Critical Findings

Beneath such qualitative features there arose some key findings which testify the effectiveness and the advantageous specificities of this hybrid solution:

- **Cold-Start Resolution:** The content-based filtering module can improve new user retention rates by ca 39% if multiple complete features are extracted for newly joined users. This is once more an evidence that the system can produce meaningful recommendations even when it has access to such sparse interaction data.
- **Diversity improvement:** The diversity of recommendations is much enhanced by the fusion model. Shannon's diversity index for recommended modules produced a 2.7X improvement over single-method recommendations, however it is unclear whether this number represents a significant difference and if it is high enough to ensure that the learner discovers content that is more varied than what they generally browse in order to engage in serendipitous and exploratory learning activities.
- **Completion Effect:** Participants (visits who followed the SfA) showed significant improvements in overall course completion, with an average 28% higher number of modules taken. This corresponds to the average number of additional modules earned per learner (or effectiveness) that is directly related to improved academic learning habits.

4.3 Ablation Study

In this work, we conduct an extensive ablation study to analyze the role of components used in hybrid architecture. To do so, I iteratively disabled one of the components (alike, conditional Middleware or Collaborative Filtering model or Content-Based Filtering) and got the relative decrease of Precison@5 at this structured hybrid recommender from raw to decalled variation.

These observations have definitely shown how effective and well-coordinated all the components are among themselves in order to achieve better hybrid model performance, which confirms that the structure is reasonably constructed. In particular, deep learning layers have the greatest singular impact, implying their capacity in representing complex structures and relationships non-linearly.

5. Discussion & Limitations

The results of our experiments also yield strong evidence that a recommended system based on the proposed deep learning hybrid model is capable of substantially improving both user engagement and the use performance in online learning platforms. The primary advantage of the method is its sophisticated hybrid architecture that reconciles collaborative filtering and content-based approaches, and it augments matrix factorization with deep neural network models. This combination enhances recommendation quality and also combats the cold-start issue, which is presented when recommending suitable items for new users/learners or freshly-added courses. Furthermore, the results provide more evidence on the efficacy of recommender system with further diversification in recommendations and notable enhancement in completion rates for module users who followed recommendations. The practical increase in course completion of 28% is practically meaningful for online educational environments. An additional 8,400 or so course completions for a school that size, and this is an impactful (from an ROI standpoint no less) increase in educational value provided by the platform. And they might capture the calculated 23%4 on learner attrition, re-enrollment, and underutilized resources as a result of reduced dropouts. Despite its strengths, our study also has some limitations:

1. **Demographic Bias:** The OULAD sample primarily consists of UK-based learners - about 85%", 69), which limits the generalisability of findings to participants that are more internationally diverse for educational contexts informed by different cultural values.
2. **Engagement Learning:** Even though engagement measures e.g., CTR, session duration and dropout patterns provide useful proxies for learner activity and persistence, they are not indicative of deeper learning products like cognitive growth, long term knowledge

retention or true skills development [31].

3. **Platform Specificity:** Although the model has not been used in other types of online learning environments (e.g., K-12 systems, corporate training platforms), many participate to these latter ones present substantial differences as compared with MOOCs in terms of data format, user interaction patterns, and instructional content.

6. Conclusion

This paper proposes and investigate a novel deep learning model hybrid recommendation scheme to enhance learner participation, retaining the level of relationship in online education. Free up the discussion between user preferences, items' attributes and hybrid recommendations is in order. Also verified the effectiveness of system using both standard offline quality measures (e.g., Precision@5, Recall@5, and NDCG), and online simulation-based real-world metrics (such as CTR, average session duration, dropout rate).

This method incorporates collaborative filtering, content-based filtering, and multiple advanced neural network building blocks, including dynamic learner embeddings, Graph Attention Networks, or multi-modal fusion, without which the system would have underperformed legacy methods and individual sub-methods.

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