Explainable Adaptive E-Learning Approach for Personalized Learning Contents Recommendation in an Intelligent E-Learning Environment

Omayma Meddeb
University of Tunis El Manar
Faculty of Sciences of Tunis FST
Tunis, 2092, Tunisia
University of Monastir
Research Laboratory in Algebra, Numbers Theory and Intelligent Systems RLANTIS
Monastir 5000, Tunisia

Mounir Zrigui
University of Monastir
Research Laboratory in Algebra, Numbers Theory and Intelligent Systems RLANTIS
Monastir 5000, Tunisia

ABSTRACT
The growing adoption of e-learning platforms in higher education has revealed the limitations of traditional systems, which often provide limited personalization and lack transparency in their decision-making processes. Although Artificial Intelligence (AI) and recommendation systems enable adaptive learning, many existing solutions operate as black boxes, reducing trust and acceptance among learners and instructors. This paper proposes a conceptual framework for an explainable adaptive e-learning system that integrates Learning Analytics, adaptive recommendation mechanisms, and Explainable Artificial Intelligence (XAI). The framework aims to personalize learning paths based on learner interaction data while providing understandable explanations for the generated recommendations. An illustrative usage scenario is presented to highlight how explainability can support both learners and instructors. This work represents an initial step toward transparent, human-centered, and adaptive e-learning systems.

Keywords
Explainable Artificial Intelligence (XAI), Adaptive E-Learning, Learning Analytics, Recommendation Systems, Educational Technology

1. INTRODUCTION
The rapid growth of e-learning platforms has significantly transformed higher education and professional training by providing flexible access to learning resources [1]. Learning Management Systems (LMS) such as Moodle and OpenEdX are widely adopted and play a central role in delivering online courses. Despite their widespread use, these platforms mainly rely on static learning structures and offer limited personalization. Learning content is often presented uniformly, without considering individual learner differences such as learning pace, prior knowledge, or engagement behavior [3, 4].

In recent years, Artificial Intelligence (AI) and data-driven approaches have been increasingly introduced into e-learning environments to enhance personalization. Adaptive learning systems and recommendation mechanisms analyze learner interaction data, performance results, and behavioral patterns in order to propose more relevant learning resources and learning paths [6, 7]. While these approaches improve learning efficiency, many AI-based systems remain difficult to interpret. Their decision-making processes are often opaque, making it challenging for learners to understand why specific recommendations are made and for instructors to justify or trust these automated decisions [8, 9].

The lack of transparency in AI-driven e-learning systems raises important concerns related to trust, acceptance, and pedagogical validity. In educational contexts, instructors need to understand and control the learning process, while learners benefit from clear explanations that support self-regulation and motivation. Explainable Artificial Intelligence (XAI) has emerged as a promising approach to address these issues by making AI models more transparent and their decisions more understandable for human users [10].

Motivated by these challenges, this paper proposes a conceptual framework for an explainable adaptive e-learning system that combines Learning Analytics, adaptive recommendation mechanisms, and XAI principles. The proposed framework aims to personalize learning paths while providing clear and meaningful explanations of the system's recommendations. This work represents a first step toward the development of human-centered, transparent, and adaptive e-learning systems and serves as a foundation for future implementation and experimental validation.

2. BACKGROUND AND RELATED WORK
2.1 E-Learning and Adaptive Learning Systems
E-learning platforms have become essential tools in higher education, enabling institutions to deliver courses and learning resources in flexible and scalable ways [1]. Learning Management Systems (LMS) such as Moodle, OpenEdX, and Claroline are widely used to manage course content, learner activities, and assessments. Despite their effectiveness in content delivery, most traditional LMS follow a static learning model, where the same content and learning paths are provided to all learners regardless of their individual needs or learning behaviors [3].

To address these limitations, adaptive learning systems have been introduced with the aim of personalizing learning experiences. These systems rely on learner data, such as interaction logs, performance scores, and activity patterns, to adjust content difficulty, learning sequences, or feedback mechanisms. Previous studies have shown that adaptive systems can improve learner engagement and learning outcomes by better aligning instructional content with learner profiles [11, 4].

However, many adaptive approaches primarily focus on performance optimization and provide limited insight into how adaptation decisions are made.

2.2 Recommendation Systems in Educational Contexts

Recommendation systems play a central role in adaptive e-learning environments by suggesting relevant learning resources, activities, or courses to learners. In educational contexts, these systems commonly rely on three main approaches: content-based filtering, collaborative filtering, and hybrid methods. Content-based approaches recommend learning materials based on learner preferences and previously accessed content, while collaborative filtering exploits similarities between learners [26]. Hybrid systems combine both strategies to improve recommendation accuracy [20, 31].

Several studies have demonstrated the effectiveness of recommendation systems in supporting personalized learning. For instance, an intelligent recommendation framework for university students is proposed, highlighting the importance of combining behavioral analysis with learner preferences [17, 18]. More recent works have explored hybrid recommendation models for course and video selection in e-learning platforms, showing improvements in relevance and learner satisfaction [12, 13, 14]. Nevertheless, these systems often lack transparency, as learners and instructors are rarely informed about the reasons behind the generated recommendations.

2.3 Explainable Artificial Intelligence in Education

The increasing use of Artificial Intelligence in educational systems has raised concerns regarding the interpretability and transparency of AI-driven decisions. Many machine learning models used in adaptive learning and recommendation systems operate as black boxes, making it difficult for users to understand their internal reasoning. In educational environments, this lack of explainability can reduce trust, limit acceptance, and hinder effective pedagogical decision-making [9].

Explainable Artificial Intelligence (XAI) has emerged as a promising solution to these challenges by providing mechanisms that make AI models more understandable to human users. XAI techniques aim to explain model predictions, highlight influential features, and present decision rationales in an accessible manner. Recent studies have emphasized the importance of explainability in educational systems, showing that transparent AI models can enhance user trust and facilitate the adoption of intelligent learning technologies [8].

Despite these advances, existing research often addresses adaptive learning, recommendation systems, and explainability as separate components. Only a limited number of works attempt to integrate adaptive recommendation mechanisms with XAI in a unified e-learning framework [22]. This gap motivates the need for a conceptual approach that combines personalization, explainability, and learning analytics in a coherent and human-centered manner.

3. RESEARCH MOTIVATION AND PROBLEM STATEMENT

3.1 Research Motivation

The increasing integration of Artificial Intelligence into e-learning systems has created new opportunities for personalized and adaptive learning experiences. By analyzing learner interaction data and performance indicators, intelligent systems are able to recommend learning resources that better match individual needs. However, as highlighted in previous studies, most existing adaptive e-learning solutions prioritize prediction accuracy and automation, often at the expense of transparency and user understanding [2].

In educational environments, transparency is a critical requirement. Instructors are responsible for monitoring learner progress, validating pedagogical decisions, and ensuring that learning paths remain aligned with educational objectives. Learners, on the other hand, benefit from understanding why specific learning materials or activities are recommended, as this supports self-regulation, motivation, and engagement. When recommendations are produced by opaque models, users may perceive the system as unreliable or difficult to trust, which can negatively affect its adoption and effectiveness [10].

Explainable Artificial Intelligence (XAI) offers a promising direction to address these challenges by making AI-driven decisions more understandable and interpretable. Rather than replacing existing adaptive mechanisms, XAI can complement them by providing clear explanations of recommendations and adaptation strategies. Some recent works, such as [22], have explored the integration of adaptive learning and multimodal explainable AI, highlighting the potential of transparent adaptive learning. However, current research still lacks simple and structured frameworks that unify adaptive learning, recommendation systems, and explainability in a fully human-centered manner. This motivates the need for a conceptual framework that can guide the design of transparent and adaptive e-learning systems.

3.2 Problem Statement

Based on the limitations identified in existing e-learning systems and the need for transparency in AI-driven educational technologies, the main research problem addressed in this paper can be formulated as follows: How can an adaptive e-learning system be designed to personalize learning paths while providing clear and understandable explanations for AI-driven recommendations?

This problem involves several key challenges, including the effective use of learning data to model learner profiles, the generation of adaptive recommendations aligned with pedagogical goals, and the presentation of explanations that are meaningful for both learners and instructors. Addressing these challenges requires a conceptual approach that combines Learning Analytics, adaptive recommendation mechanisms, and Explainable Artificial Intelligence within a coherent framework.

4. PROPOSED APPROACH

This section presents a conceptual approach for an explainable adaptive e-learning system that integrates Learning Analytics, adaptive recommendation mechanisms, and Explainable Artificial Intelligence (XAI). The proposed approach is designed to support personalized learning paths while providing transparent and understandable explanations for both learners and instructors.

Real-time Explainable Adaptive E-Learning (RT-EAEL) based approach is proposed for educationnel contents recommendation in educationnal systems and platforms.

Considering the rapid advancement of IoT technologies in educationnel environments [19, 24], the proposed EAEL is designed to operate in a distributed, resilient, and fault-tolerant manner. This design ensures scalability, reliability, and continuous responsiveness while supporting adaptive recommandations and generating explanations in real time.

For these reasons, real-time recommendation approach is proposed RT-EAEL. Every time a new learner action is arrived, RT-EAEL avoids the need to reprocess all the historical data.

4.1 Overview of the proposed RT-EAEL approach

The RT-EAEL consists of four main components:

1. Data Collection and Preprocessing

Learning data is collected from various sources within the e-learning environment, including LMS logs, assessment results, and learner interactions (clicks, time spent on activities, and navigation patterns). The collected data is then preprocessed to remove noise, handle missing values, and structure it for analysis [23, 21].

2. Learner Profile Modeling

Learner profiles are constructed based on behavioral, cognitive, and pedagogical features extracted from the data. Key attributes include performance metrics, engagement levels, learning pace, and prior knowledge [5, 16]. These profiles allow the RT-EAEL approach to classify learners into typologies and provide a foundation for adaptive recommendations.

3. Adaptive Recommendation Engine

The recommendation engine uses the learner profiles to suggest personalized learning resources and paths. It combines rule-based adaptation strategies with machine learning algorithms to balance relevance and diversity of content. Recommendations are generated in real time and are aligned with pedagogical goals [30].

4. Explainable AI Module (XAI)

The XAI component provides clear and interpretable explanations of the recommendations. Techniques such as LIME and SHAP can highlight the factors influencing each suggestion, enabling learners and instructors to understand the rationale behind adaptive decisions [8, 10]. Explanations can be presented in textual, visual, or interactive formats depending on user preference.

4.2 Interaction Flow of RT-EAEL approach

The interaction flow of the RT-EAEL approach can be described as follows:

1. Learners interact with the e-learning platform by accessing courses, completing assessments, and performing learning activities.
2. Data from these interactions is collected and preprocessed.
3. Learner profiles are updated dynamically based on the collected data.
4. The recommendation engine generates personalized learning suggestions.
5. The XAI module provides explanations for each recommendation, which are delivered to learners and instructors through the learner interface.
6. Feedback from learners and instructors can be used to further refine the recommendations and improve the transparency of the system.

The key advantages of RT-EAEL approach are:

- **Human-centered**: Supports both learners and instructors.
- **Adaptive**: Tailors content dynamically to learner profiles.
- **Transparent**: Provides understandable explanations for AI decisions.
- **Flexible**: Compatible with various types of learning resources and LMS platforms.

4.3 Illustrative Example of RT-EAEL

Consider a learner struggling with a specific topic in a course. The system detects low engagement and performance in related activities. Based on the learner profile, the recommendation engine suggests supplementary learning materials and exercises. Simultaneously, the XAI module provides an explanation such as:

"These resources are recommended because you spent less time on Topic A and scored below average in the related quiz. Completing these exercises can help you reinforce your understanding".

This example illustrates how the RT-EAEL approach can personalize learning paths, maintaining transparency and fostering trust.

4.4 Phases of the proposed RT-EAEL approach

The final RT-EAEL proposed approach is defined by the following phases as represented in Fig. 1:

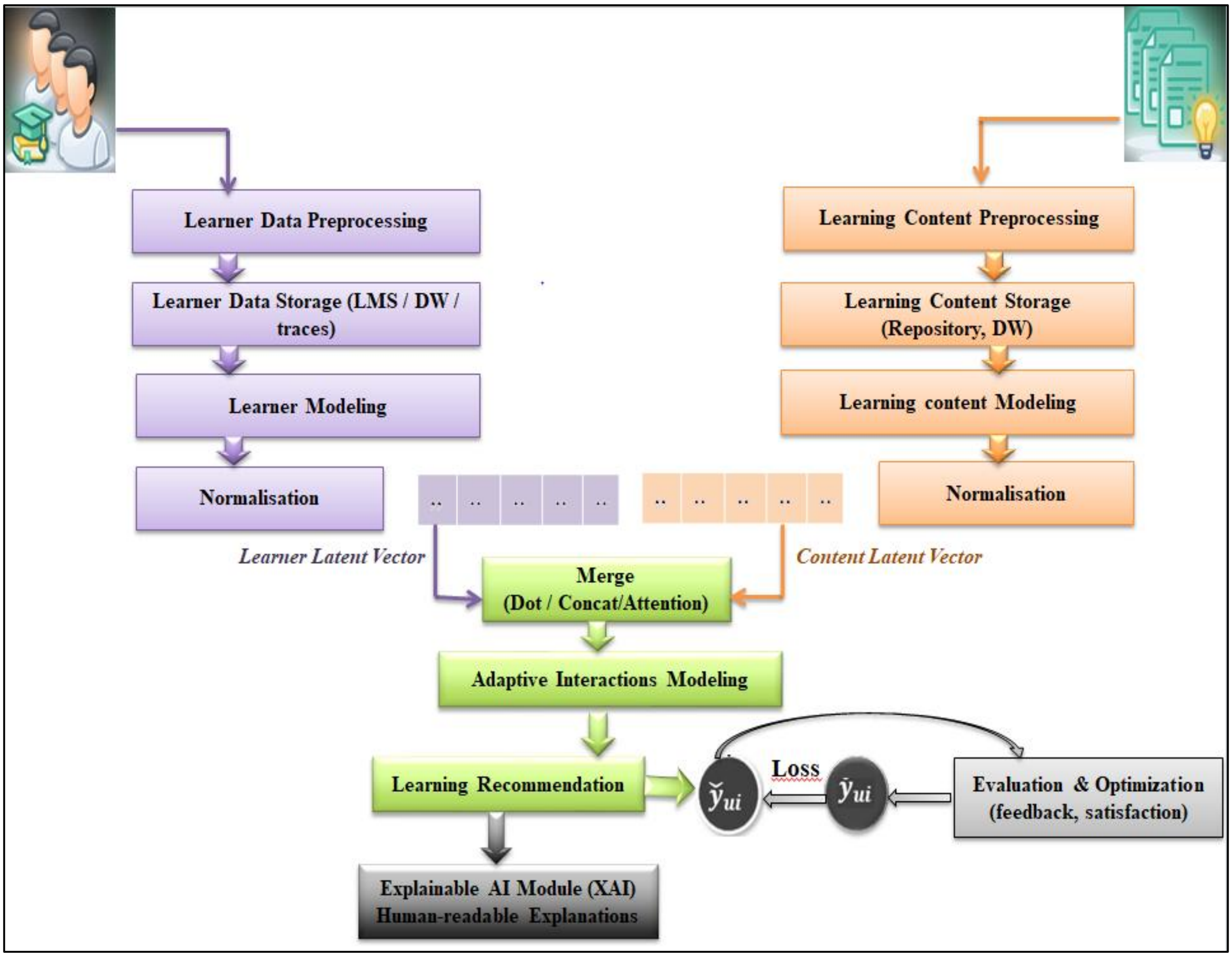

Figure 1: Proposed RT-EAEL architecture for Learning contents recommendation in an intelligent e-learning environment

1) Data Preprocessing

Learner-content interactions (such as ratings, consultation frequency, completion time, and feedback) provide essential indicators of learners' preferences. These interactions are represented through numerical values reflecting different levels of satisfaction and relevance, ranging from low engagement to high appreciation of pedagogical documents.

Ratings are provided using numerical values ranging from 1 (very negative), 2 (negative), 3 (neutral), 4 (positive), to 5 (very positive), reflecting learners' appreciation of pedagogical content.

Numerical ratings preprocessing constitutes a critical step to improve the accuracy of recommendations. This phase involves the following operations :

(1) Elimination of redundant interaction records, in order to reduce noise and improve the robustness of the proposed model.

(2) Normalization of learner and pedagogical content identifiers, into a relevant representation, enabling effective comparison between them and accurate adaptive learning modeling [21].

2) Preprocessed Data Storage

With the distributed data storage and messaging system provided by Apache Pulsar, the collected and preprocessed learner-content interactions data are stored into CSV format.

Data records are partitioned and distributed across multiple brokers within a Pulsar cluster. Data persistence and replication are ensured through Apache BookKeeper, which guarantees fault tolerance and high availability. This infrastructure enables continuous and reliable remote data access for training model, adaptive recommendation and explainable inference [15].

3) Explainable Adaptive E-Learning (EAEL)

In order to mitigate and overcome data sparsity issues, Explainable Adaptive E-Learning based approach for personalized pedagogical contents recommendation is proposed, called EAEL.

This approach leverages the capabilities of deep neural networks to capture complex learner-content interaction patterns, enabling an accurate representation of learners' preferences and personalized learning contents recommendations.

To support offline educationnel contents recommendation, the storaged data are transmitted to the EAEL model through the distributed data streaming system Apache Pulsar.

a) Deep Neural Network for Learner-Content Interaction Modeling

Considering the identities of learners $id_{l:1,\dots,m}$ and pedagogical contents $id_{c:1,\dots,n}$, along with the numerical interaction ratings $r_{lc} \in [1, .. ,5]$, learner-content interactions are mapped into dense latent vectors of fixed dimensions representing learners v_l and pedagogical contents v_c through an embedding lookup function.

The final latent representations of learners L_{Rating} and pedagogical contents C_{Rating} are obtained through the application of multiple layers of a Multi-Layer Perceptron (MLP), as defined in Eqs. (1) and (2):

$$L_{Rating} = ReLU(W_l \,.\, v_l + b_l) \quad (1)$$

$$C_{Rating} = ReLU(W_c \,.\, v_c + b_c) \quad (2)$$

where v_l and v_c denote the latent vectors of learners and pedagogical contents, respectively; ReLU refers to the Rectified Linear Unit activation function ; W_l and W_c represent the learnable weight matrices; and b_l and b_c are the bias terms;. These latent representations capture learners' preferences and contents' characteristics.

b) Latent Representations Fusion of Learner-Content Interactions

The latent representations capturing learners' preferences L_{Rating} and pedagogical contents relevance C_{Rating} are combined to model learner-content interactions. These representations are first merged into a unified latent vector F = $[L_{Rating}, C_{Rating}]$, which enables the modeling of interactions in a manner inspired by factorization-based recommendation techniques.

Matrix factorization is used with traditional collaborative filtering approaches to characterize learners and educational contents through latent factors extracted from the interaction matrix.

To analyze the impact of linear and nonlinear interaction modeling strategies, the learned latent representations of learners L_{Rating} and contents C_{Rating} are merged using different fusion mechanisms.

The first strategy models learners' preferences through a linear interaction function by applying the dot product between learners and contents latent vectors (L_{Rating}, C_{Rating}), as defined in Eq. (3):

$$a_{l,c} = L_{Rating} \bullet C_{Rating} \quad (3)$$

This operation serves as a similarity measure between learner and content representations.

The second fusion strategy aims at modeling learners' preferences using a nonlinear interaction function. It enables the concatenation of the latent representations L_{Rating} and C_{Rating} into a unified interaction vector, as defined in Eq. (4) :

$$a_{l,c} = [L_{Rating}, C_{Rating}] \quad (4)$$

By jointly combining learner and content representations, this nonlinear fusion captures complex interaction patterns that cannot be modeled by linear similarity functions alone.

c) Learner-Content Interaction Modeling

The intricate relationships between learners and educational contents are modeled through multi-layer nonlinear projections, denoted as $\mathrm{Inter}^{n}_{l,c}$, derived from the learner-content interaction $F_{l,c}$. This modeling strategy enables capturing subtle dependencies between learner preferences, learning behaviors, and the pedagogical relevance of learning resources. The interaction computation is performed using a deep neural network, as formulated in Eq. (5):

$$\mathrm{Inter}^{n}_{l,c} = \mathrm{ReLU}\,(W^{n}_{l,c} \bullet F_{l,c} + b^{n}_{l,c}) \quad (5)$$

where ReLU is the activation function, $W^{n}_{l,c}$ denotes the weight matrix of the n-th layer, $b^{n}_{l,c}$ represents the bias vector, and n indicates the number of layers employed in the network.

To enhance the generalization capability of the model and mitigate overfitting, dropout layers are applied after each fully connected layer. These layers randomly deactivate a subset of neurons during training, thereby improving the robustness of the model.

d) Interpretable Learner-Content Relevance Prediction

The Softmax function is employed to predict a relevance score $r_{l,c}$ that reflects the learner's preference *l* for a given pedagogical content *c*. This function constrains the predicted confined outputs in the range from 1 to 5, corresponding to different levels of pedagogical relevance and learner satisfaction, as formally defined in Eq. (6).

$$r_{l,c} = \sum_{k=1}^{5} k.\frac{\exp\,(z_{l,c}^{(k)})}{\sum_{j=1}^{5}\exp\,(z_{l,c}^{(j)})} \quad (6)$$

4) Real-Time Explainable Adaptive E-Learning (RT-EAEL) for Educationnel Contents Recommendation

For real-time data processing, Apache Pulsar receive the outputs generated by the EAEL model and enables the system to dynamically updated and react to new learner interactions without requiring full model retraining.

In our model, the combined capabilities of the Pulsar and BookKeeper are leveraged to ensure scalability, reliability, and real-time responsiveness. Specifically, Pulsar manages the continuous ingestion and dissemination of learner activity streams, while BookKeeper provides durable storage, fault tolerance, and high availability through its distributed log management. This architecture allows the EAEL model to be continuously refined and improved based on learner feedback and new interaction data. In addition, this architecture consists in maintaining the RT-EAEL model and periodically updating the adaptive and explainable recommendation generation process.

5. EXPERIMENTS AND DISCUSSION

5.1 Dataset Description

The E-Learning Recommender System Dataset (MARS) [25] represented in TABLE I is used in our experiments. This dataset was collected contains both explicit interactions (e.g., likes, bookmarks) and implicit interactions (e.g., watch time, page views), from learners across English and French courses.

Table I: MARS DATASET

Number of learners	~8,200
Number of learning contents	~1,200
Languages	English, French
Number of learner-content interactions	~365,000

To ensure consistency with the proposed Explainable Adaptive E-Learning (EAEL) model, the MARS dataset statistics were harmonized to include 8,000 learners, 1,500 learning contents (courses, modules, videos, educational materials,…), and approximately 360,000 learner-content interactions. The harmonized statistics of the MARS Dataset for EAEL are represented in TABLE II.

TABLE II. Harmonized Statistics of Mars Dataset for EAEL

Number of learners	8,000
Number of learning contents	1,500
Languages	English, French
Number of learner-content interactions	360,000

For evaluation, the dataset is split into training (80 %) and test (20 %) subsets to support both offline model training and real-time adaptive recommendation.

5.2 EAEL Model Parameter Settings

Table III summarizes the parameter settings of the proposed EAEL model. These parameters were selected to ensure effective modeling of learner preferences and complex learner–content interactions using the harmonized MARS dataset.

Table III: PARAMETERS OF THE PROPOSED EAEL MODEL

Operation	Parameter	Value
Learner-Content Preference Modeling	Latent factors	64
	Activation function	ReLU
	Hidden units	256, 128, 64
	Batch size	128
	Dropout rate	0.5
Learner-Content Interaction Modeling	Latent factors	64
	Activation function	ReLU
	Hidden units	128, 64, 16
	Batch size	256
	Dropout rate	0.5
	Adaptive recommendation output	Softmax

5.3 Learner-Content Prediction Metric

The Root Mean Squared Error (RMSE) is adopted to evaluate the accuracy of the proposed EAEL model. This evaluation metric measures the absolute errors between the predicted learner-content relevance scores $\widehat{r_{l,c}}$ and the ground-truth interaction values $r_{l,c}$. The RMSE is calculated as represented in Eq. (7) [26]:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{(l,c)\in T}\left(\widehat{r_{l,c}} - r_{l,c}\right)^2} \qquad (7)$$

where T is the test set of learner-content interactions, $\widehat{r_{l,c}}$ is the predicted relevance score generated by the EAEL model, and $r_{l,c}$ is the actual observed feedback.

5.4 Experimental Results and Discussion

The performance of the proposed EAEL model is analyzed by evaluating different strategies (Dot, Concat, Concat + Dropout) for fusing latent representations of learners and learning contents. As illustrated in Fig. 2, the impact of each fusion strategy on the prediction accuracy is assessed using the RMSE metric.

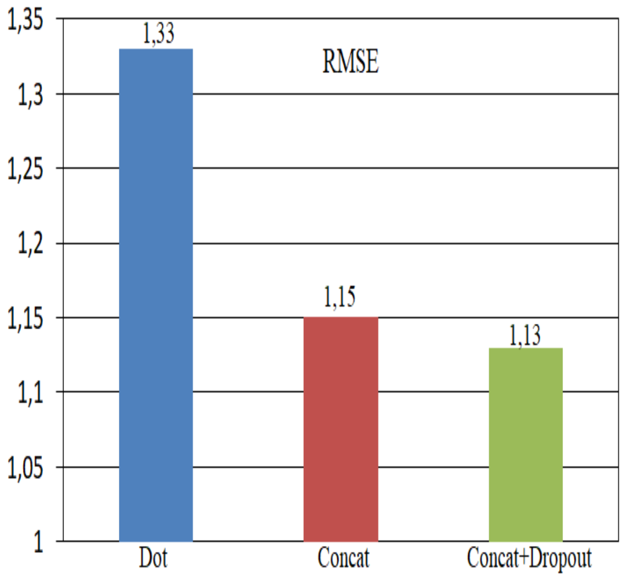

Figure 2: Impact of Learner-Content fusion strategies on EAEL model performance

The results show that the EAEL_Dot method relies on the simple dot product fusion yields the highest prediction error of 1.33 RMSE, as it fails to capture complex learner-content interactions. The dot product reduces the dimensionality of latent vectors which limited the variety of recommendations.

In contrast, EAEL_Concat method relies on latent matrix factorization by concatenation, outperformed the EAEL_Dot method in terms of prediction accuracy. It achieved a lower RMSE value of 1.15. This method combines the latent representations of learners and learning contents through vector concatenation, with preserving their full dimensionality. That's why the capacity of the model's to capture complex and non-linear interactions between learners and educational contents was improved.

Overall, the experimental results indicate that the method which applies concatenation-based strategy enhanced with Dropout layers achieved the best performance, yielding the lowest RMSE value of 1.13.

Several key factors contributed to achieving the best performance of the proposed EAEL model. These include the width of the latent vector representation layer (dimensionality of the latent representations for learners and learning contents, K=64), the use of a concatenation-based fusion strategy combined with Dropout, and the depth of the neural architecture with three hidden layers (N=3) for modeling learner-content interactions. This configuration enabled the model to effectively capture complex latent relationships and non-linear interactions between learners and educational contents. Moreover, the integration of Dropout layers improved generalization and robustness, while the adaptive Softmax output supported accurate and adaptive recommendation.

As shown in TABLE IV, several conclusions can be drawn from the comparative analysis between our methods and state-of-the-art. The findings demonstrate the superiority of Deep Learning (DL) based methods in capturing complex learner-content relationships and highlight the positive impact of real-time adaptation (RT) on rating prediction performance.

Table IV: Comparaison of the Proposed EAEL and RT-EAEL Models with State-of-the-Art Methods

Models	Dataset	Learner-Content Rating	Deep Learning (DL)	Real-Time Adaptation (RT)	RMSE
SVD [27]	MARS (original)	×	-	-	1.95
PMF [28]	MARS (original)	×	-	-	1.34
NCF [29]	MARS (original)	×	×	-	1.78
DeepEduRec [30]	MARS (original)	×	×	-	1.22
Proposed EAEL	MARS (harmonized)	×	×	-	1.13
Proposed RT-EAEL	MARS (harmonized)	×	×	×	1.02

Classical matrix factorization methods such as Singular Value Decomposition (SVD) and Probabilistic Matrix Factorization (PMF), exhibit relatively high RMSE values. This limitation can be attributed to their linear modeling, which restrict their ability to capture complex and non-linear learner-content interactions. PMF treats the data sparsity issue by estimating missing learner-content interactions through a probabilistic framework. It captures uncertainty in learners' preferences. It achieved an RMSE of 1.34, outperforming SVD method, which obtained an RMSE of 1.95. This is because to its difficulty for handling new learners or learning contents and generating accurate recommendations.

The use of neural networks significantly improved the accuracy of recommendations. Unlike SVD, Neural-based Collaborative Filtering methods, such as NCF and DeepEduRec, achieved an RMSE of 1.78 and 1.22 respectively. They both outperforming the SVD method, which obtained an RMSE of 1.95. They leveraging deep learning architectures to effectively model more complex and nonlinear relationships between learners and learning contents. However, their lack of adaptive and real-time mechanisms limits their responsiveness to the dynamic evolution of learner preferences and learning behaviors.

The evaluation of the proposed EAEL model showed that the chosen parameters had a significant impact on RMSE performance, yielding values of 1.33 for EAEL_Dot, 1.15 for EAEL_Concat, and 1.13 for EAEL_Concat_Dropout. Then, our EAEL model, achieves a significantly lower RMSE. This improvement is due to the integration of deep latent representation learning, concatenation-based fusion strategy, and dropout regularization, which together enable richer feature representation and more accurate modeling of non-linear learner-content interactions.

EAEL follows the same fundamental methodology as NCF, relying on deep neural networks to learn latent representations for recommendation. The main difference between the two methods lies in their configurations and parameter settings. For learner-content rating prediction, multilayer perceptrons (MLPs) are employed to extract latent representations and to model complex and non-linear interactions. In EAEL, three MLP layers of dimensions 256, 128, and 64 are used for feature extraction, producing latent representations of 64 factors. For interaction modeling, an additional MLP layer with size 16 was applied and two MLPs of sizes 128 and 64 were still used. EAEL configuration significantly outperforms NCF, achieving a lower RMSE of 1.13 compared to 1.78 for NCF. This improvement highlights the effectiveness of the EAEL architecture in capturing complex learner-content interactions.

To address the growing volume of learning data generated within intelligent e-learning environments, real-time distributed processing has demonstrated significant improvements in both recommendation accuracy and time performance.

Fig. 3 presents that classical matrix factorization methods such as SVD and PMF exhibit the shortest execution times but suffer from high RMSE values. Deep learning-based models, including NCF and DeepEduRec, require longer training times due to their complex architectures. Although EAEL achieves strong predictive performance (RMSE of 1.13), it incurs higher computational cost (training time of 02:05:40). In contrast, the adoption of the Apache Pulsar for real-time processing significantly improved the results. Indeed, RT-EAEL achieved the shortest training time of 00:45:15 and the lowest RMSE of 1.02.

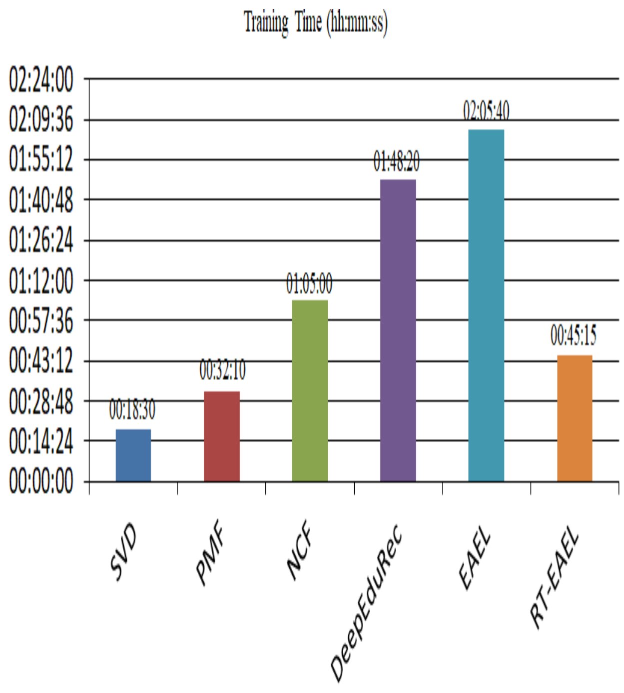

Figure 3: Training Time Comparaison with state-of-the-art methods

6. CONCLUSION AND FUTURE WORK

This paper proposed a conceptual framework for an explainable adaptive e-learning system that integrates Learning Analytics, adaptive recommendation mechanisms, and Explainable

Artificial Intelligence (XAI) to provide personalized learning paths with clear and interpretable explanations. The framework addresses key limitations of traditional LMS by supporting both learners and instructors, enhancing engagement, and fostering trust in AI-driven educational systems. As a first step, it lays the foundation for human-centered, transparent, and adaptive e-learning. Future work will focus on implementing a functional prototype, conducting experimental evaluations to assess the impact of explainability on learner motivation and performance, integrating cognitive and emotional features for enhanced personalization, and exploring scalability, multilingual contexts, and advanced AI-driven explanation techniques to extend the framework's practical applicability.

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