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RESEARCH ARTICLE

Learning-Motivation-Boosted Explainable Temporal Point Process Model for Course Recommendation

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ABSTRACT Course recommendation is vital for improving students' learning efficiency. In the learning process, students' interests evolve, learning cycles and course scheduling are closely related to temporal information. However, previous course recommendation methods discard it as irrelevant, leading to poor recommendation performance. In addition, the lack of explainability of the course recommendations reduces students' engagement and trust in online learning. To solve two problems, this paper proposes a Learning-motivation-boosted Explainable Temporal point process model for Course Recommendation (LETCR). Firstly, LETCR considers the timestamps in interaction records as absolute time and the sequence of records as relative time, and it calculates the different contributions of historical interaction records to the recommendation results. Secondly, LETCR proposes four factors that affect students' course selection from the perspective of learning motivation: interest preference, follow relationship, conformity and popular course. Finally, LETCR models these with a temporal point process, so as to improve model's explainability. Extensive experiments on the MOOCCourse dataset show that LETCR outperforms other advanced recommendation models by 7.09% and 9.28% on R@10 and NDCG@5, respectively, and has high explainability.

INDEX TERMS Course recommendation, temporal point process, e-learning, explainable recommendation, learning motivation.

I. INTRODUCTION

The advent of educational technology has simplified students' access to courses via online platforms [1]. However, with the burgeoning number of available courses, information overload has become a significant issue [2]. In response, course recommendation (CR) systems have garnered substantial interest among researchers, aiming to bolster learning efficiency [3].

Researchers have developed various models for CR [4], [5], including models based on collaborative filtering [6], models based on GNN [7] and models based on reinforcement learning [8] etc. Current CR methods have achieved good results but still face two problems:

(1) These methods only utilize static student-course interactions as input and assume only previously learned courses and their order will affect the next recommended course [9]. Jiang et al. [10] input interactions into a modified RNN. Wang et al. [11] input interactions as a bipartite graph. However, students' preferences change over time and temporal features in interactions provide crucial information, such as students' learning cycles. For example, in Figure 1, both student A and student C studied advanced mathematics. So CR system may suggest study linear algebra at t7. It is noteworthy that student A studied advanced mathematics at t6, while student C studied at t1. Their interaction time will influence the recommendation result differently.

(2) Many researchers have opted for complex model architectures to achieve higher accuracy, often at the expense of explainability—a key factor in user satisfaction with recommender systems [12]. CR should not only recommend

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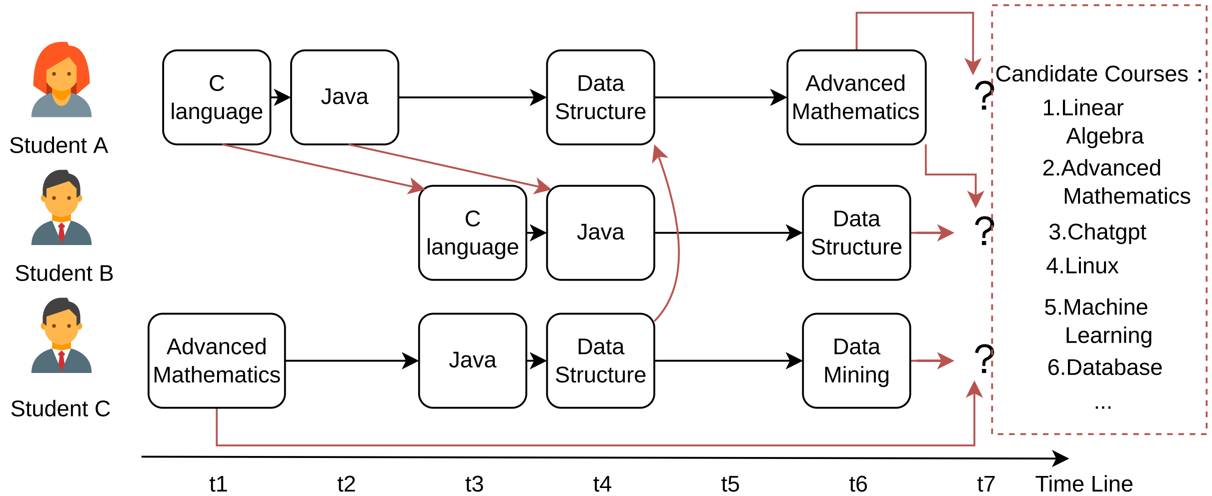

FIGURE 1. Examples of Student Learning Sequences. The black arrows represent the order in which students studied the courses. The red arrow represents the impact on students' course selection.

suitable courses, but also explain students' motivations for choosing them. Such potential information is contained in student's historical interaction. For example, if Student A, seen as a role model by Student B, chooses a particular course, it might influence Student B's choices. Similarly, if a course like ChatGPT gains popularity at t7, it's more likely to be recommended. Previous CR methods have overlooked these nuanced factors that influence course selection.

In this paper, we propose a Learning-motivation-boosted Explainable Temporal point process model for Course Recommendation (LETCR). To address problem 1, temporal features are introduced. We explore two useful temporal patterns: absolute time and relative time. Absolute time models the month and date of each interaction. Relative time models the sequence of interactions. To address problem 2, we explore the factors that influencing course selection based on learning motivation. According to self-determination theory (SDT) [13], [14], the motivation is divided into intrinsic and extrinsic learning motivations. Intrinsic learning motivation reflects students' interest and satisfaction, which is manifested in CR as interest preference. Depending on degree, extrinsic learning motivation can be divided into external regulation, intake regulation, identity regulation, and integration regulation. External pressure and the desire to avoid punishment are the main sources of the first two, manifested in CR as popular course and conformity. Identity regulation and integration regulation are the transition from extrinsic to intrinsic motivation, when students realize the value of learning by observing role models, reflected in CR as follow relationship. Since temporal point process (TPP) can model the impact of past events on the present, we take it as backbone. Five parameters, combined with the base rate specific to TPP, will bring rich explainability to recommendation results.

The principal contributions of this work are outlined as follows:

(1) We introduce a Learning-Motivation-Boosted Explainable Temporal Point Process Model for Course Recommendation (LETCR), which leverages a temporal point process (TPP) as its core architecture. This model integrates both temporal features and learning motivation factors, aiming to improve both the accuracy and the explainability of course recommendations.

(2) To maximize the utilization of temporal information, our model distinguishes between absolute and relative time. We employ an attention mechanism to assess how past interactions based on these temporal patterns influence current recommendations.

(3) Grounded in Self-Determination Theory (SDT), our model identifies and integrates four motivational factors into the recommendation process: interest preference, follow relationship, conformity, popular course. Model use the attention module to calculate the values of the four factors, and further input into TPP to make predictions.

(4) Rigorous testing on real-world datasets confirms that our model outperforms existing advanced course recommendation systems. Additionally, a detailed case study is presented to illustrate the model's high level of explainability.

II. RELATIVE WORK

A. COURSE RECOMMENDATION

The early CR is mainly based on collaborative filtering [15], [16], [17], which assums that students with similar interests in the past will also choose the same course in the future [18]. For example, Symeonidis and Malakoudis [19] made use of external resource information (user skills) and adopted the matrix decomposition method to recommend courses. This type of approach lays the theoretical foundation for future research.

In recent years, CR methods based on deep learning have made great progress in accuracy due to the strong expressive power of neural networks [20], [21], [22]. The mainstream deep CR methods are divided into RNN-based and GNN-based. Jiang and Pardos [23] used RNN to analyze students' learning sequences chronologically to predict recommended courses. The method based on RNN can capture the sequential information of the learning process. But there are potential information implicit in student-course interactions. Researchers have started incorporating GNN into CR to capture such information. Wang et al. [24] proposed a hyperedges graph attention network to mine similarity relationships among learners. Wang et al. [11] proposed a Top-N personalized CR model, utilizing GNN to capture higher-order relationships between courses. GNN can address RNN's limitations but overlooks crucial temporal features.

In the latest study, researcheres introduced reinforcement learning into CR [25], [26]. As models become increasingly complex, few researchers have been able to preserve the temporal features in the interaction behavior while fully leveraging latent information to enhance the explainability of recommendation results.

B. TEMPORAL POINT PROCESS

TPP can explicitly incorporate temporal information and correlations between events using conditional intensity functions, offering greater explainability [27]. TPP has been widely used in event prediction, including employee check-in prediction [28], aviation market prediction [29].

TPP assumes past events can increase the probability of future events [30]. This phenomenon is known as the self-motivating effect, which additive in past events and decays exponentially over time. In recent years, some researchers have applied Hawkes process in recommendation systems. Wang et al. [31] proposed an attention TPP for music recommendation. This model can dynamically adjust the influence of past listening records on future recommendations. Wang et al. [32] employed the multidimensional Hawkes process to enhance sequential recommendation accuracy by incorporating users' long and short-term preferences. Zhou et al. [33] combined hyperbolic space and Hawkes process to tackle scale-free data distribution, proposing a novel method for generating user-item interaction sequences.

A clear advantage of TPP is the ability to provide meaningful explanations, especially valuable in educational scenarios [34]. Explainability in education not only help students in understanding learning content but also enhances the scientific aspect of educational decision-making.

C. EXPLAINABLE RECOMMENDATION

Providing clear explanations can enhance users' acceptance of recommended content [35], [36], [37]. The explainability of recommendation models is categorized into model-agnostic approaches and model-intrinsic [38].

Model-agnostic method trains a recommendation model and an explainable model separately to provide reasons for the recommendations. Tan et al. [39] used a counterfactual module to provide straightforward explanations for model decisions. Yera et al. [40] used model-agnostic approaches to enhance the explainability of nutritional recipe recommendation. However, explanations are not directly derived from the recommendation model, leading to no guarantee of the credibility of the provided explanation.

Model-intrinsic method aims to establish a decision-making process based on specific reasons from the beginning. Chen et al. [41] extracted various user-item interaction paths from the knowledge graph and consolidated them into common behavioral rules, which serve as explanations. Similarly, Shimizu et al. [42] proposed an enhanced knowledge graph attention network model, which utilized item side information to achieve a direct interpretation by visualizing attention scores. Model intrinsic method obtains explanations directly from the recommended model, however, this often comes at the expense of reduced model accuracy.

Research on enhancing the explainability of recommendation models will focus on utilizing model intrinsic methods to maintain good performance.

D. DIFFERENCES

Our work differs significantly from existing work in several ways:

(1) Existing advanced CR algorithms either utilize RNN to obtain the sequential order relationship in the learning sequence, or utilize graph neural networks to capture the potential information between the student and the course, and are unable to consider the contribution of the potential information in the past interactions to the recommendation results from the temporal perspective, which affects the recommendation accuracy. In this paper, we not only consider the sequential order in the learning sequence, but also combine the absolute time of interaction. Under the premise of considering two temporal patterns, the influence of potential information in past interactions on recommendation results is calculated through the attention layer.

(2) In the model-intrinsic approach, previous studies used too much side information to train the model improving the interpretability of the model, but reducing the recommendation accuracy of the model. In contrast, our study takes advantage of TPP to view course selection behavior as a result of students making choices because of specific motivations based on self-determination theory. Students' motivations for choosing courses will bring convincing explanations for the recommendation results while maintaining good accuracy.

III. PRELIMINARY

A. DEFINITION OF COURSE RECOMMENDATION

This section gives some basic definitions as follows:

1) INTERACTION RECORD

Let $U = \{u_1, u_2, \ldots, u_m\}$, $C = \{c_1, c_2, \ldots, c_n\}$ represent the set of m users n courses. A record is a triple $(u_j, c_i, t_l) \in U \times I \times T$, which represents student u_j studied course c_i at t_l.

2) INTERACTION SEQUENCE

Let S be the set of all students' interaction sequences. For a student uj, an interaction sequence is denoted as

TABLE 1. Key mathematical symbols and descriptions.

Symbol	Description
U, C, T	students set, courses set and time set
u, c, t	a student, a course and a timestamp
$U \in R^{\|m\|*d}, C \in R^{\|n\|*d}$	students embedding matrix and courses embedding matrix
e_{uj}, e_{ci}, e_{tL}	student u_j's embedding, course c_i's embedding, timestamp t_L's embedding
$e_{At}, e_t^m, e_t^d, e_{Pt}$	timestamp t_L's absolute time embedding, month-level embedding, day-level embedding, relative time embedding
d	the dimension of embedding
S_{uj}	student u_j's behavior squence
ξ	the number of sequence sampling length
$\lambda_{ci\|uj(t_{L+1})}$	the recommendation probability preference of u_j for c_i at time t
$\mu_{ci,uj}$	the base rate of student u_j for c_i
k	the kernel function that calculates the influence of historical events
η_u, η_c	the decay rate of students' historical influence, the decay rate of courses' historical influence
ILM, ELM	Intrinsic-learning-motivation score and extrinsic-learning-motivation score
β^i, β^e	adaptive weights of student u_j's ILM and ELM
u_j^{fr}	student u_j follows' a students
u_j^c	students who have a conformity influence on student u_j at recommendation time
c^{pc}	popular courses at recommendation time
$K^{ip}, K^{fr}, K^c, K^{pc}$	interest preference score, follow relationship score, conformity score, popular course score
w_1, w_2, w_3, w_4	trainable model parameters

$S_{uj} = \{(c_{uj1}, t_1), (c_{uj2}, t_2), \ldots, (c_{ujL}, t_L)\}$, each bracket is an interaction containing the course and timestamp of the interaction.

3) COURSE RECOMMENDATION TASK

Given a student $u_j \in U$ and a historical sequence $S_{uj} \in S$. The goal of the task is to predict the course c_i that best matches student u_j at t_{L+1}.

For ease of presentation, the key symbols and their descriptions are summarized in Table 1.

B. TEMPORAL POINT PROCESS MODELING

TPP allows modeling event sequences by capturing the temporal dependencies between events. An event (u_j, c_i, t_l) is a interaction between student u_j and course c_i at t_l.

TPP models the probability of an event occurring at t as $\lambda(t)$, also known as the intensity function. In this paper, we select one of the most famous TPP-the multidimensional Hawkes process [43]. The multidimensional Hawkes process allows for the modeling of sequences of events and the effects of interactions between events in a sequence. The conditional intensity function in it depicts the arrival rate of past events to the current event. It is defined as follows:

$$\lambda(\mathrm{t}) = \mu + \int_0^t \beta \mathrm{k}(\mathrm{t}-\mathrm{s})\mathrm{dN}(\mathrm{s}) \tag{1}$$

μ is the base rate of the current event's fundamental probability, unaffected by past occurrences. β is the excitation rate of the past events on the current event. k(t-s)dN(s) is the kernel function describes how historical event N(s) affects the current event at t. In general, the excitation is positive, additive on historical events, and decays exponentially over time. A conditional intensity function $\lambda(t)$ represents the incidence of an event, defined as the probability of an event occurring within a small time window $[t, t + \Delta t)$.

We aim to determine the probability of event c_i occurring in the recommended course, given the student interaction sequence S_{uj}.

C. LEARNING MOTIVATION

We categorize course selection motivation into intrinsic and extrinsic motivation according to SDT, and identify four factors.

Intrinsic learning motivation reflects students' interest, enjoyment, and satisfaction, originating from the course's meaning and value. Students select courses based on their interest, driven by curiosity and inquisitiveness. Intrinsic learning motivation in this paper refers to:

1) INTEREST PREFERENCE

Students' own interest preference is a unique feature and evolves over time. We take the course sequence S_{uj} as a reflection of interest preference, and calculate the score K^{ip} of student u_j's interest preference with the candidate course c^i (see 4.3.2 for calculation details).

Extrinsic learning motivation is categorized into external regulation, intake regulation, identity regulation and integration regulation. Identity and integration regulation are the closest to intrinsic motivation, often stemming from students' desire to good grades and the role modeling effect of excellent students. External and intake regulation come entirely from external rewards or punishment, usually from social pressure and competition. Extrinsic learning motivation of this paper includes: follow relationship, conformity, popular course.

2) FOLLOW RELATIONSHIP

If student A is a role model for student B, the probability that student B takes the course which student A had taken will increase. We call this behavior a follow relationship. Based on interaction sequences S_u, we find students u_j^{fr} who had taken the same course before student u_j taken. The score K^{fr} of the follow relationship of student u_j is calculated by u_j and u_j^{fr} (see 4.3.3 for calculation details).

3) CONFORMITY

Students tend to follow the choices of others to avoid standing out or conflicting with the majority, which is a psychological tendency to seek belonging and social acceptance. We search for a number of students u_j^c who had recently interacted before the recommendation time t_{L+1}. The score K^c of conformity is computed by u_j and u_j^c (see 4.3.3 for calculation details).

4) POPULAR COURSE

Students prefer courses that are popular and in demand to stay current with societal development. We search for a number of courses c^{pc} that had recently generated interactions before the recommendation time t_{L+1}. The score K^{pc} of popular course is computed by candidates c_i and c^{pc} (see 4.3.3 for calculation details).

IV. METHOD

A. OVERVIEW

In this section, the learning-motivation-boosted explainable temporal point process model for CR will be presented in detail. The model framework, as illustrated in Figure 2, comprises three main parts: (1) Embedding layer: All students and courses are embedded as vectors. Temporal features are embedded in absolute and relative time, then spliced together to form time vectors (the schematic diagram will be shown in Section IV-B). (2) Learning-motivation-enhanced TPP Modeling Layer: Learning motivation is divided into intrinsic and extrinsic learning motivation, and the scores for each factor are obtained through the attention layer according to the intensity function of the temporal point process. (3) Prediction Layer: The final recommendation probability is obtained by the score value of each factor calculated in the previous module and is iteratively updated by the binary cross entropy loss function.

TPP serves as the backbone framework of this model, modeling the impact of historical student interactions on the next recommendation. In order to increase interpretability, four motivations influencing students' course selection are proposed and used as a kernel function to predict the probability of recommendation. The formulas are as follows:

$$\lambda_{\mathrm{ci|uj}}(\mathrm{t_{L+1}}) = \mu_{\mathrm{ci,uj}} + \beta^i * \mathrm{ILM} + \beta^e * \mathrm{ELM} \tag{2}$$

$\lambda_{ci|uj}(t_{L+1})$ is the probability of recommending course c_i to u_j at t_{L+1}. $\mu_{ci,uj}$ is base rate. ILM and ELM are intrinsic learning motivation score and extrinsic learning motivation score. β^i, β^e are the adaptive weights.

B. EMBEDDING LAYER

1) STUDENT AND COURSE EMBEDDING

Due to the sparse of students and courses, it is common to transform them into a low-dimensional space. Two distinct embedding layers are used to map students and courses into low-dimensional hidden spaces. Let $U \in R^{|U|*d}$ denote the user embedding matrix generated by the user embedding layer, and e_{uj} is the embedding vector of student u_j. Here d is the embedding size. Let $C \in R^{|n|*d}$ denote the user embedding matrix generated by the user embedding layer, e_{ci} is the embedding vector of course c_i.The student and course vectors are randomly initialized and updated iteratively with the loss function.

2) ABSOLUTE TIME EMBEDDING

To generate timestamp embeddings, temporal information needs to be considered at multiple granularities to enrich the time representation. We consider granularities at the month and day levels. The absolute time vector of timestamp t_L is represented as:

$$\mathrm{e}_{\mathrm{At}_L} = \mathrm{e}_{\mathrm{t}_L}^m + \mathrm{e}_{\mathrm{t}_L}^d \tag{3}$$

$\mathrm{e}_{\mathrm{t}_L}^m$ and $\mathrm{e}_{\mathrm{t}_L}^d$ are vectors of months and days extracted from the month and day embedding matrices M^m and M^d based on t_L. $\mathrm{e}_{\mathrm{At}_L}$ is the absolute time vector with timestamp t_L. The month and day embedding matrices are randomly initialized and iteratively updated along with the loss function.

3) RELATIVE TIME EMBEDDING

To capture the relative order of items in the student or course domain, a position vector is added. In this paper, we utilize the positional coding method proposed by Vaswani et al. [44], which can be extended to longer sequence lengths without adding extra parameters. The method is defined as follows:

$$\mathrm{e}_{\mathrm{Pt}_{(pos,2\ i)}} = \sin\left(\frac{pos}{10000^{2i/d}}\right) \tag{4}$$

$$\mathrm{e}_{\mathrm{Pt}_{(pos,2\ i+1)}} = \cos\left(\frac{pos}{10000^{2i/d}}\right) \tag{5}$$

pos denotes the position of the word, i denotes the dimension, and d denotes the dimension size. In position encoding, each even dimension corresponds to a sine curve, and each odd dimension corresponds to a cosine curve. e_{Pt} is the relative time vector represents the timestamp t_L. The relative time vector remians fixed and does not update iteratively with the loss function.

The absolute and relative time vectors are combined as depicted in Figure 3 to obtain the final time vector representation:

$$\mathrm{e}_{t_L} = \mathrm{e}_{\mathrm{At}_L} + \mathrm{e}_{\mathrm{Pt}_L} = \mathrm{e}_{\mathrm{t}_L}^m + \mathrm{e}_{\mathrm{t}_L}^d + \mathrm{e}_{\mathrm{Pt}_L} \tag{6}$$

C. LEARNING-MOTIVATION-ENHANCED TPP MODELING LAYER

1) BASE RATE MODELING

Regardless of what courses a student has taken previously, all courses have a specific probability of being recommended,

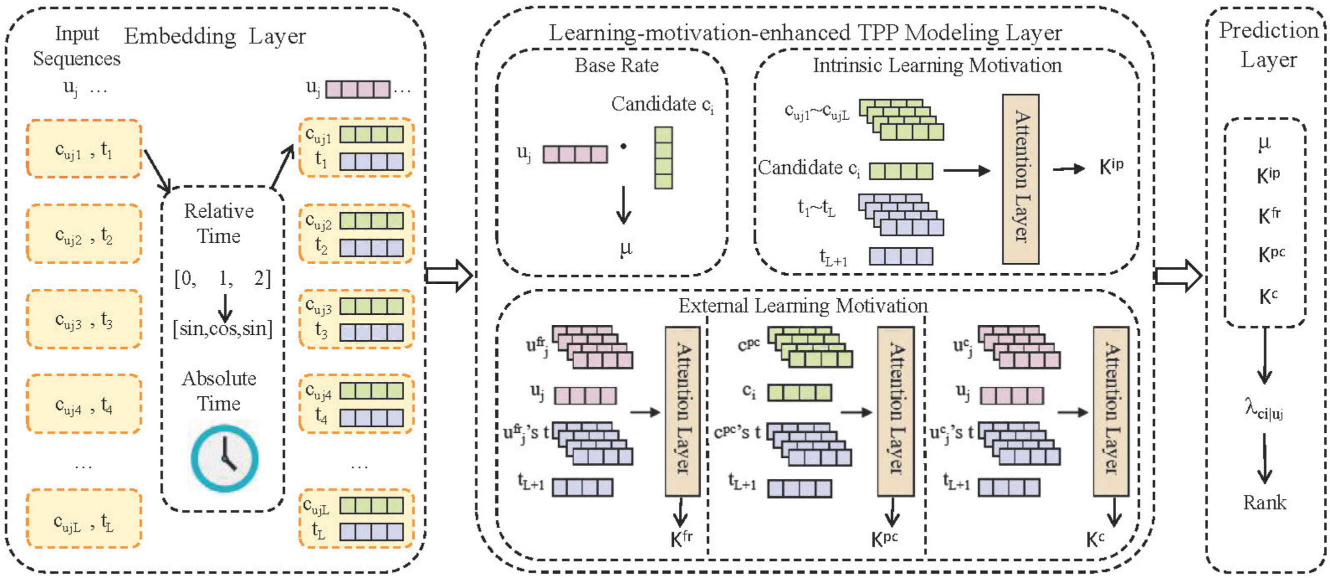

FIGURE 2. Framework for learning-motivation-boosted explainable temporal point process model.

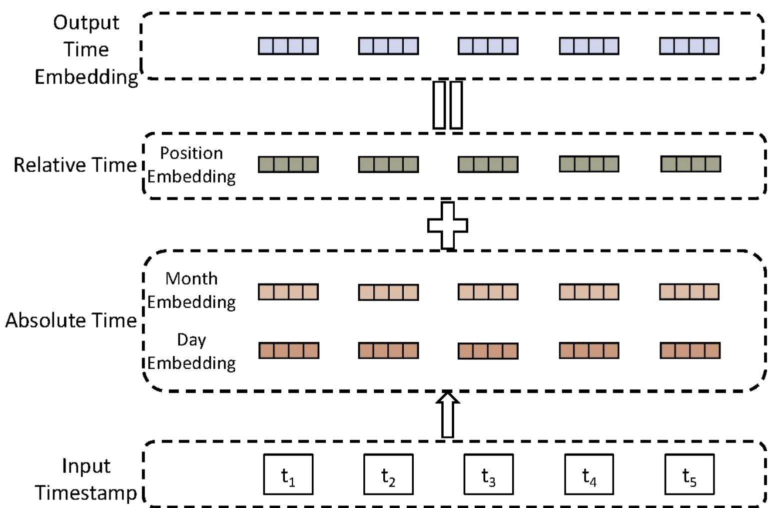

FIGURE 3. Time embedding module.

called the base rate. To model this, we input the embedding of students and courses into the intensity function, as shown in Equation 7:

$$\mu_{ci,u\,j} = e_{uj}^{T} e_{ci} \tag{7}$$

e_{uj} is the embedding of student u_j and e_{ci} is the embedding of course c_i. $\mu_{ci,u\,j}$ represents the probability of recommending course ci to student uj without considering any historical interactions. Other metrics, like cosine similarity and Euclidean distance, can also be used between vectors in addition to the dot product.

2) INTRINSIC LEARNING MOTIVATION MODELING

To evaluate the influence of historical learning records on recommendation outcomes, kernel function modeling is employed from the perspective of learning motivation. To modeling intrinsic learning motivation, we consider the influence of students' interest preferences.

The student's historical interactions are stored in S_u, from which we obtain the student's interest preferences. For ease of calculation, all users uniformly choose the latest ξ interaction records. If the length exceeds ξ, delete superfluous; if the length is smaller, fill it with zero vectors. After this, the value of interest preference is calculated with the candidate course c_i. Specifically, the attention weight $a_{s_{uj},c\,i}$ of each history course to the candidate course is initially calculated, which is obtained from the course vector and the time vector as shown in Eq. 8. Then, interest preference score is aggregated by Eq.11.

$$\begin{aligned} a_{s_{uj},c\,i} &= \operatorname{softmax}\left(s_{uj,c\,i} + t_{uj,c\,i}\right) \\ &= \frac{\exp\left(s_{ujr,c\,i} + t_{ujr,c\,i}\right)}{\sum_{r=1}^{\xi} \exp\left(s_{uj,c\,i} + t_{uj,c\,i}\right)} \end{aligned} \tag{8}$$

$s_{uj,c\ i}$ is

$$s_{uj,c\ i} = \mathrm{ReLU}\left(W_1 e_{s_{uj}} + W_1 e_{ci}\right) \tag{9}$$

$e_{s_{uj}}$ is the embedding of student u_j history course, and W_1 is the trainable weight matrix. $t_{uj,c\ i}$ is

$$t_{uj,c\ i} = \exp\left(-\eta_c\left(e_t - e_t^{s_{uj}}\right)\right) \tag{10}$$

η_c denotes the decay rate of historical influence, which is a learnable parameter. e_t is the embedding of the recommendation time, $e_t^{s_{uj}}$ is the interaction time embedding of student u_j's ξ history courses.

$$k^{ip}_{uj,c\ i} = \sum_{r=1}^{\xi} a_{s_{uj}r,c\ i} e_{s_{uj}r} \tag{11}$$

The final value for intrinsic learning motivation is:

$$\mathrm{ILM} = k^{ip}_{uj,c\ i} \tag{12}$$

3) EXTRINSIC LEARNING MOTIVATION MODELING

Aiming to model extrinsic learning motivation, we examine students' follow relationship, conformity and popular course.

Students tend to follow their good or close classmates when choosing courses. The interaction sequence S_{uj} of student u_j is compared with the interaction sequences of other students. If student u_v has taken a course that student u_j has taken before, student u_v is one of the following relations of student u_j. Again, a fixed length ξ is chosen here. The attention weight $a_{u_j^{fr},u\ j}$ is used to aggregate the information of following relations u_j^{fr} to get following relationship score.

$$a_{u_j^{fr},u\ j} = \mathrm{softmax}\left(s_{u_j^{fr},u\ j} + t_{u_j^{fr},u\ j}\right) = \frac{\exp\left(s_{u_j^{fr}r,u\ j} + t_{u_j^{fr}r,u\ j}\right)}{\sum_{r=1}^{\xi}\exp\left(s_{u_j^{fr},u\ j} + t_{u_j^{fr},u\ j}\right)} \tag{13}$$

$s_{u_j^{fr},u\ j}$ is

$$s_{u_j^{fr},u\ j} = \mathrm{ReLU}\left(W_2 e_{u_j^{fr}} + W_2 e_{uj}\right) \tag{14}$$

$e_{u_j^{fr}}$ is the embedding of the student u_j's follow relationship, and W_2 is the trainable weight matrix. $t_{u_j^{fr},u\ j}$ is

$$t_{u_j^{fr},u\ j} = \exp\left(-\eta_u\left(e_t - e_t^{u_j^{fr}}\right)\right) \tag{15}$$

η_u denotes the decay rate of historical influence, which is a learnable parameter where the influence of each user decays at a different rate. e_t is the embedding of the recommendation time, $e_t^{u_j^{fr}}$ is the interaction time embeddingt of student u_j's ξ followed students.

$$k^{fr}_{u_j^{fr},u\ j} = \sum_{r=1}^{\xi} a_{u_j^{fr}r,c\ i} e_{u_j}{}^{fr} r \tag{16}$$

In addition, students in the neighborhood can influence course selection, a phenomenon known as conformity. In this paper, we identify ξ students who have recently interacted before the recommendation time as u_j^c.The attention mechanism is utilized to assess each student's influence, resulting in a conformity score.

$$a_{u_j,u\ j} = \mathrm{softmax}\left(s_{u_j^c,u\ j} + t_{u_j^c,u\ j}\right) = \frac{\exp\left(s_{u_j^c r,u\ j} + t_{u_j^c r,u\ j}\right)}{\sum_{r=1}^{\xi}\exp\left(s_{u_j^c,u\ j} + t_{u_j^c,u\ j}\right)} \tag{17}$$

$s_{u_j^c,u\ j}$ is

$$s_{u_j^c,u\ j} = \mathrm{ReLU}\left(W_3 e_{u_j^c} + W_3 e_{uj}\right) \tag{18}$$

$e_{u_j^c}$ is the embedding of students who have recently interacted before the recommendation time, W_3 is the trainable weight matrix. $t_{u_j^c r,u\ j}$ is

$$t_{u_j^c,u\ j} = \exp\left(-\eta_u\left(e_t - e_t^{u_j^c}\right)\right) \tag{19}$$

$$k^c_{\mathbf{u}_j^c,u\ j} = \sum_{r=1}^{\xi} a_{\mathbf{u}_j^c r,c\ i} e_{\mathbf{u}_j^c r} \tag{20}$$

Finally, the popularity of courses also influences their choices. We filter ξ courses with recent interactions before the recommended time as c^{pc}. Similarly the attention mechanism is used to judge the impact of each popular course to get popular course score.

$$a_{c^{pc},c\ i} = \mathrm{softmax}\left(s_{c^{pc},c\ i} + t_{c^{pc,c\ i}}\right) = \frac{\exp\left(s^{pc}_{c_{r,c\ i}} + t^{pc}_{c_{r,c\ i}}\right)}{\sum_{r=1}^{\xi}\exp\left(s^{pc}_{c,c\ i} + t^{pc}_{c,c\ i}\right)} \tag{21}$$

$s_{c^{pc},c\ i}$ is

$$s^{pc}_{c,c\ i} = \mathrm{ReLU}\left(W_4 e_{c^{pc}} + W_4 e_{ci}\right) \tag{22}$$

$e_{c^{pc}}$ is embedding of popular courses, W_4 is the trainable weight matrix. $t_{c^{pc,c\ i}}$ is

$$t_{c^{pc},c\ i} = \exp\left(-\eta_c\left(e_t - e_t^{c^{pc}}\right)\right) \tag{23}$$

$$k^{pc}_{c^{pc},c\ i} = \sum_{r=1}^{\xi} a_{c^{pc},c\ i} e^{pc}_{c_r} \tag{24}$$

The final value of extrinsic learning motivation is:

$$\mathrm{ELM} = k^{fr}_{u_j^{fr},u\ j} + k^c_{\mathbf{u}_j,u\ j} + k^{pc}_{c^{pc},c\ i} \tag{25}$$

D. PREDICTION LAYER

The values of base rate, intrinsic learning motivation and extrinsic learning motivation were calculated in subsection IV-C, and then used in Equation 2 to obtain the recommended strength $\lambda_{ci|uj}(t_{L+1})$. Finally, the results are normalized using a sigmoid to get the final recommendation probability $\widetilde{\lambda}_{ci|uj}(t_{L+1})$.

$$\widetilde{\lambda}_{ci|uj}(t_{L+1}) = \text{sigmoid}\left(\lambda_{ci|uj}(t_{L+1})\right) \tag{26}$$

To optimize the parameters of the model, binary cross entropy is used as the loss function:

$$L = -\left[\sum_{(u,c,t)\in p^{+}} \log \widetilde{\lambda}_{ci|uj}(t_{L+1}) + \sum_{(u,c,t)\in p^{-}} \log\left(1 - \widetilde{\lambda}_{ci'|uj}(t_{L+1})\right)\right] \tag{27}$$

p^{+} indicates positive examples, and p^{-} is negative examples. All parameters and embeddings are learned through backpropagation in an end-to-end training manner.

V. EXPERIMENT AND RESULT ANALYSIS

In this section, detailed experiments will be conducted to demonstrate the advantages of our model. The following questions are studied in our research:

RQ1: How does our model perform compared to other advanced baselines?

RQ2: Do absolute time modeling and relative time modeling improve recommendation performance?

RQ3: When considering only intrinsic or extrinsic motivation, how does it impact recommendation performance?

RQ4: How do the three hyperparameters, the dimension of the embedding, the length of the sequence sampling and the learning rate, affect the performance of the model?

RQ5: Can our model provide an explanation for the recommendation results?

A. DATASET

The experiment is conducted on a real dataset MOOCCourse. MOOCCourse is obtained from the academy online platform. The data starts from October 1, 2016 and ends on March 31, 2018. We mainly analyzed the students, courses and temporal information in the MOOC data, in which each user took more than 2 courses. The data contains a total of 82,535 students and 1302 courses, with 458,454 student-course interaction behaviors, and the average number of user interactions is 5.55. The dataset is divided into a training set and a test set by 8:2 based on their chronological order.

B. BASELINES

We compare our model with the following baseline models.

POP: This method recommends courses based on popularity, and prioritizing recommends popular courses. This method is straightforward yet highly valuable in specific scenarios.

BPR [45]: This method is a classical top-k item recommendation method based on Bayesian Personalized Ranking. It models the order of candidate items by pairwise ranking loss without considering sequence pattern.

GRU4REC [46]: This method uses RNN-based gating units to predict the transfer probability of items from session sequences. This model is the first application of RNN to Session-based Recommendation.

PinSage [47]: A recommendation model that utilizes graphs to generate user/item feature representations. The model is the first graph algorithm to apply GCN to an industrial-grade recommender system.

TP-GNN [33]: An advanced MOOC CR method that captures higher-order semantic relationships between courses via GCN and uses an attention mechanism to generate the final course representation.

EHTPP [11]: Each user-item interaction is treated as an event in a hyperbolic space, and a TPP is used to model the probability of the event occurring.

C. EVALUATION METRICS

To facilitate direct comparison with previous work, we use two evaluation metrics that are widely used in the top-k recommendation and personalized ranking tasks [48].

Recall, R@K, denotes the percentage of correctly predicted items among the top k recommended items over all positive examples. R@K is defined as follows:

$$R@k = \frac{\left|\text{pred}_u @k \cap \text{pos}_u\right|}{\left|\text{pos}_u\right|} \tag{28}$$

$pred_u@k$ are k recommended courses, pos_u are courses that students really like.

Normalized discounted cumulative gain, NDCG@k, is also called the order-sensitive accuracy rate. First the discounted cumulative gain (DCG) needs to be calculated:

$$DCG@k = \sum_{i}^{k} \frac{r(i)}{\log_2(i+1)} \tag{29}$$

r(i) denotes the score of the ith item, predicted correctly as 1. Next, normalization needs to be done with IDCG@k:

$$IDCG@k = \sum_{i}^{k} \frac{1}{\log_2(i+1)} \tag{30}$$

Finally, we get NDCG@k:

$$NDCG@k = \frac{DCG@k}{IDCGk} \tag{31}$$

D. EXPERIMENT SETTINGS

In this paper, LETCR is implemented using the Pytorch accelerated by GeForce RTX 4090 24G GPU. Random initialization is performed for all parameters. Adam is used as the optimizer for the model, with a weight decay rate set to 0.001 and the size of a batch is set to 128. The hyperparameters are set as follows: learning rate is set to 0.001, embedding dimension is set to 256, and sequence sampling length ξ is set to 5. All the parameters of the baseline model are consistent with their settings in the paper, keeping them as they were when the best performance was obtained.

TABLE 2. Overall recommendation performance (%).

Models	R				NDCG			
	5	10	15	20	5	10	15	20
POP	7.28	12.43	19.34	25.48	5.8	7.79	9.86	11.67
BPR	21.67	34.54	39.05	42.46	13.97	18.04	20.33	19.42
GRU4REC	24.87	34.04	38.05	43.56	14.3	18.04	21.01	20.33
PinSage	24.99	37.83	44.96	49.79	14.7	19.9	22.19	23.58
TP-GNN	26.35	38.82	46.11	50.85	15.51	20.83	22.47	23.91
EHTPP	30.73	48.93	61.02	70.03	29.73	36.29	41.71	45.23
LETCR	32.07	52.4	64.57	74.68	32.49	39.32	45.21	48.59
Improve	4.36	7.09	5.82	6.64	9.28	8.35	8.39	7.43

E. PERFORMANCE COMPARISON (RQ1)

Table 2 summarizes the performance of various CR models. Our model demonstrates superior performance compared to other baseline models. Compared with the optimal baseline model (EHTPP), R@5, R@10, R@15, and R@20 improved by 4.36%, 7.09%, 5.82%, and 6.64%, respectively; NDCG@5, NDCG@10, NDCG@15, and NDCG@20 improved by 9.28%, 8.35%, 8.39%, and 7.34%, respectively. From the results, the following observations can be summarized:

· Traditional recommendation algorithms (i.e., POP and BPR) achieve the worst results. POP bases its recommendations solely on the frequency of item occurrence, overlooking student preferences and attributing all course selections to popularity. BPR models students' preferences solely through matrix decomposition, which cannot capture the sequential patterns of the students' learning process. Due to the sparse nature of the MOOCCourse dataset, it is necessary to mine the interactions for potential information to enhance student and course representations. LETCR addresses this limitation by considering students' motivations for course selection from various aspects and incorporating temporal features.

· Deep learning-based methods enhance recommendation accuracy. GRU4Rec is the first RNN-based session recommendation model that highlights the importance of temporal features in sequence modeling. However, RNN can only capture the sequence between adjacent courses, lacking the ability to model absolute time. This limitation causes the model to struggle in learning information like students' learning cycles and course-specific attributes. GNN-based approaches are more effective than RNN-based approaches. PinSage and TP-GNN map all courses or learners into a graph and update each node's embedding by aggregating its neighbors' representations, allowing them to learn higher-order information among courses or students. Our model mines the rich information between students and courses, while also utilizing temporal information to enhance accuracy.

· Temporal-based models yield optimal results. Both LETCR and EHTPP belong to the temporal point process. EHTPP considers that recommendation data forms a tree-like hierarchy and follows a scale-free distribution, where the number of neighbors of a node grows exponentially. Therefore, EHTPP maps the data to hyperbolic space instead of Euclidean space. The MOOCCourse dataset belongs to short sequences compared to traditional recommendation algorithms. This is due to students having fewer interactions on average, which partially alleviates this issue. Our proposed LETCR model considers both relative and absolute time's impact on recommendation results, leading to superior performance compared to EHTPP.

F. ABLATION STUDY (RQ2&RQ3)

To validate the importance of temporal embedding and learning motivation modeling in LETCR, this section investigates the performance of four LETCR variants.

LETCR-w/o-at: This focuses solely on relative positional order of students and courses in the interaction, discarding absolute time modeling.

LETCR-w/o-rt: This focuses solely on absolute time modeling, discarding the relative positional order of students and courses in the interaction.

LETCR-w/o-ilm: This focuses solely on extrinsic learning motivation, and believes that influence students' course selection are follow relationship, conformity and popular course.

LETCR-w/o-elm: This focuses solely on intrinsic learning motivation and assumes that influences students' course selection is their own interest preferences.

The results of the experiment are shown in Figure 4, from which we get the following observations:

· Using temporal information in interaction records provides a significant performance improvement. LETCR improves over LETCR-w/o-at by 3.31% and 1.25% on R@5 and NDCG@20. LETCR improves over LETCR-w/o-rt by 5.03% and 3.82% on R@5 and NDCG@20. This highlights the importance of modeling temporal information, and the improvement from relative time modeling is greater than that from absolute time modeling. The reason is that MOOCCourse dataset interactions are relatively sparse, and students' learning cycles and course-specific attributes are not well represented. This also shows that sequence-based models such as GRU4REC consider the role of relative time more than BPR, thus bringing performance improvement. However, LETCR integrating two patterns of time has better effect than the method considering only one kind, indicating that the influence of these two patterns of time on the result is not equivalent, and should be used together.

· Considering both intrinsic and extrinsic learning motivation significantly improve performance. LETCR improves by 23.63% and 11.67% over LETCR-w/o-ilm on R@5 and NDCG@20. LETCR improves by 10.70% and 3.56% over LETCR-w/o-elm on R@5 and NDCG@20. Most CR algorithms focus on intrinsic motivation, but they only lead to sub-optimal results. For example, TP-GNN considers higher-order relationships between courses, but is still limited. The number of students studying on MOOC platforms is relatively small, and there are interferences from the external environment in selecting courses. POP takes into account the influence of popular courses, and completely ignores the interests of students themselves, which is also undesirable. The method proposed in this paper combines internal learning motivation and external learning motivation to capture the incentive of students to choose courses.

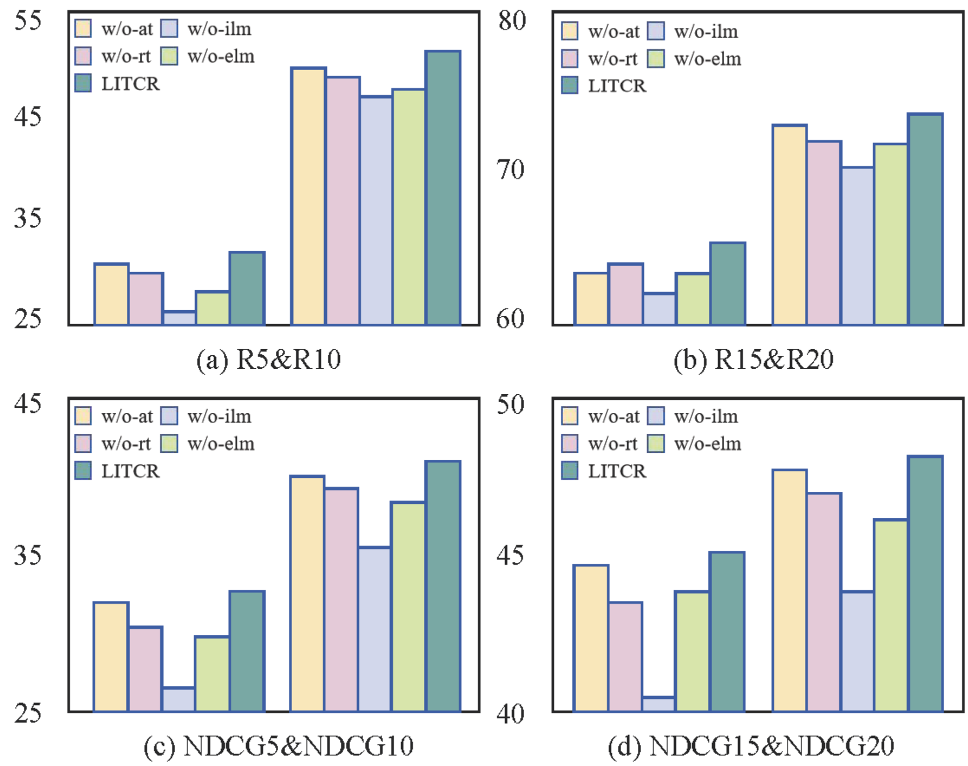

FIGURE 4. Comparison of four variations on MOOCCourse.

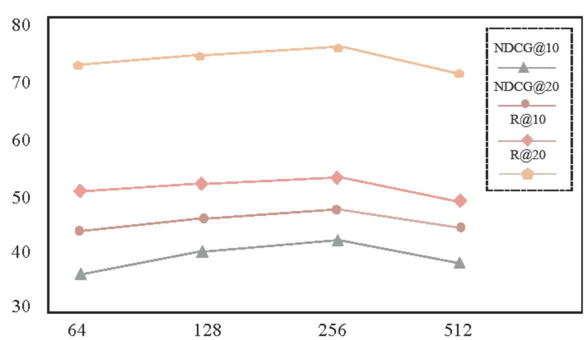

FIGURE 5. Dimension of embedding.

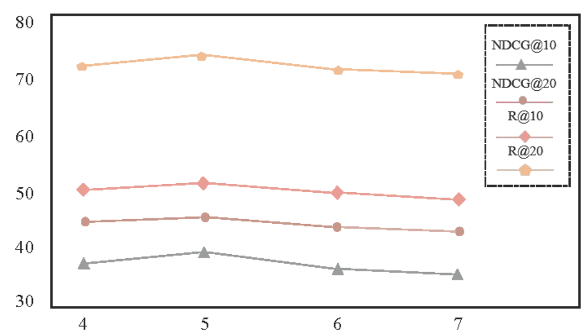

FIGURE 6. Length of sequence sampling.

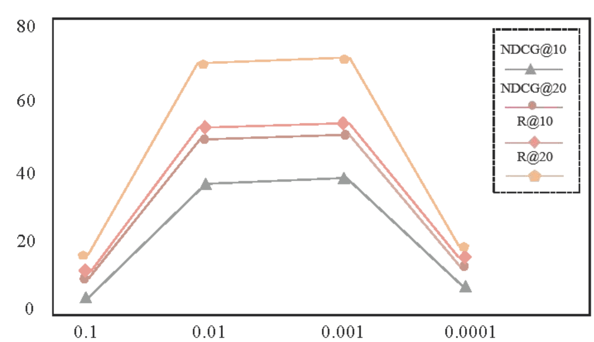

FIGURE 7. Learning rate.

G. HYPER-PARAMETER STUDY (RQ4)

In this section, we examine how the embedding dimension, sequence sampling and learning rate impact the performance of LETCR. Analysis is performed on the data set by means of control variables, that is, only the analysis variables are changed while keeping the other parameters in the model constant.

Embedding dimension d is adjusted from {64, 128, 256, 512} to examine the effect of it on the model performance. Figure 5 illustrates how this parameter affects the performance of LETCR recommendations on the MOOCCourse dataset. When embedding dimension is less than 256, R@10, R@20, NDCG@10, and NDCG@20 increase with embedding dimension, indicating that the expressive power of LETCR gradually improves. When the embedding dimension exceeds 256, R@10, R@20, NDCG@10 and NDCG@20 start to decline. To some extent, a larger embedding dimension helps the model learn richer information, thereby improving performance. However, when the embedding

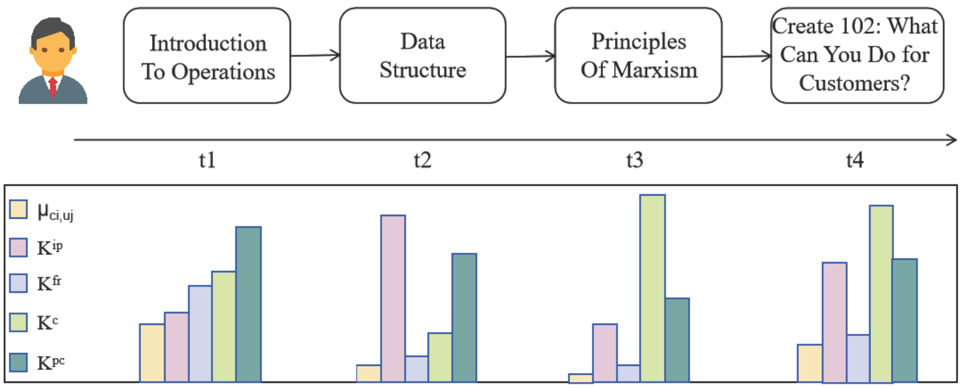

FIGURE 8. **The example of u_a for the illustration of LETCR's explainability.**

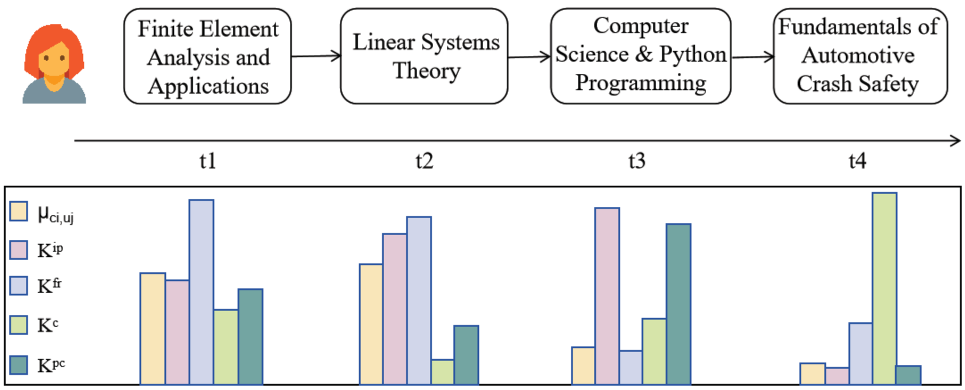

FIGURE 9. **The example of u_b for the illustration of LETCR's explainability.**

dimension reaches a certain value, overfitting problems will be caused, and the performance of the model begins to decline.

The impact of the length of sequence sampling ξ on the performance of the model is explored. Leave the other hyperparameters unchanged, adjusting ξ from 4,5,6,7. As you can see from Figure 6, the initial increase leads to better performance, because considering more related items leads to richer information.However, when exceeding 5, the aggregation process tends to introduce too much noise, which degrades the performance of the model. The average number of student interactions on the MOOCCourse dataset is 5.55, so 5 is also a reasonable value, which can achieve high performance at a lower computational cost. The length of the sequence sampling is usually related to the data set, and the data set in the education field is relatively sparse and the sampling length is relatively small.

The impact of learning rate on model performance is explored. Keeping all other hyperparameters constant, the learning rate is adjusted from $\{0.1, 0.01, 0.001, 0.0001\}$. It is clearly observed in Figure 7 that the model performance drops sharply when the learning rate is 0.1 and 0.0001. A learning rate that is too large causes the parameter update amplitude to increase, resulting in the model oscillating around the optimal solution and failing to converge stably. A small learning rate slows down convergence of the objective function and may lead to getting stuck in a local minimum. As depicted in the figure, optimal results are obtained with a learning rate of 0.001.

H. EXPLAINABILITY ANALYSIS (RQ5)

Previous experiments have demonstrated that LETCR enhances recommendation precision compared to other baseline models. In addition, LETCR can provide students with reasonable explanations regarding learning motivation. This section uses real examples from the MOOCCourse dataset to demonstrate how LETCR offers explanations. We randomly select the behavioral sequences of student u_a and student u_b as shown in Figures 8 and 9, respectively. In these figures, histograms plot the values of all potential influencing factors, including $\mu_{ci,uj}$, K^{ip}, K^{fr}, K^{c}, K^{pc}. The higher the score of an influencing factor, the taller the histogram, showing its greater contribution to the recommendation results. From the graph, we have the following observations:

· From a single interaction, our model can directly understand students' motivation for choosing a course in each time step. At t1, u_a chose Introduction to Operations due to its popularity, while at t2, u_a chose Data Structure based on personal interest. However, in t3 and t4, student u_a followed the crowd trend rather than their own interests. Similarly, u_b chose Finite Element Analysis and Applications and Linear Systems Theory at t1 and t2 mainly due to the interest and imitation of role models. At t4, many people around u_b chose Fundamentals of Automotive Crash Safety, so u_b also chose this course. Based on these observations, it helps us to understand why students choose courses at specific times.

· From multiple interactions, our model also reveals the dynamics of students' motivation in selecting courses. Student u_a followed the crowd most of the time. Only at t2 did student u_a make a choice that matches interests. It can be inferred that student u_a's interest is in technology, while specialization might be management. Student u_b's choices in the first three moments were driven by interest, but in t4 u_b almost completely followed the crowd. Reduced enthusiasm for learning is a common issue with online learning platforms. Based on these observations, it helps students discover the reasons behind their course selection and reminds them to choose courses that align with their interests.

VI. CONCLUSION AND FUTURE WORKS

In this paper, we propose an explainable temporal point process model for course recommendation. Our model refines temporal features into absolute and relative time modeling to investigate how interaction records at different times affect recommendation results. We introduces TPP into CR to address explainable issue in the education domain. Based on the self-determination theory, the model attributes students' motivations for course selection to four factors: interest preference, follow relationship, conformity and popular course. Extensive experiments on the MOOCCourse dataset demonstrate that incorporating temporal features significantly enhances recommendation performance. Our model also provides intuitive insights into students' course selection motivations and how they change over time.

We plan to improve this work in this way. Due to the serious sparsity of MOOCCourse, making it challenging for the model to accurately capture students' true interests, leading to a performance bottleneck. In future work, we will explore data enhancement techniques to alleviate the issue of sparsity.

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REFERENCES

[1] M. I. Al-Twijri, J. M. Luna, F. Herrera, and S. Ventura, "Course recommendation based on sequences: An evolutionary search of emerging sequential patterns," *Cognit. Comput.*, vol. 14, no. 4, pp. 1474–1495, Jul. 2022.

[2] M. Zhang, S. Wu, X. Yu, Q. Liu, and L. Wang, "Dynamic graph neural networks for sequential recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 5, pp. 4741–4753, May 2023.

[3] A. H. Nabizadeh, J. P. Leal, H. N. Rafsanjani, and R. R. Shah, "Learning path personalization and recommendation methods: A survey of the state-of-the-art," *Expert Syst. Appl.*, vol. 159, Nov. 2020, Art. no. 113596.

[4] G. George and A. M. Lal, "Review of ontology-based recommender systems in e-learning," *Comput. Educ.*, vol. 142, Dec. 2019, Art. no. 103642.

[5] A. Khalid, K. Lundqvist, and A. Yates, "A literature review of implemented recommendation techniques used in massive open online courses," *Expert Syst. Appl.*, vol. 187, Jan. 2022, Art. no. 115926.

[6] A. Esteban, A. Zafra, and C. Romero, "Helping university students to choose elective courses by using a hybrid multi-criteria recommendation system with genetic optimization," *Knowl.-Based Syst.*, vol. 194, Apr. 2020, Art. no. 105385.

[7] Y. Zhu, H. Lu, P. Qiu, K. Shi, J. Chambua, and Z. Niu, "Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization," *Neurocomputing*, vol. 415, pp. 84–95, Nov. 2020.

[8] Y. Lin, F. Lin, W. Zeng, J. Xiahou, L. Li, P. Wu, Y. Liu, and C. Miao, "Hierarchical reinforcement learning with dynamic recurrent mechanism for course recommendation," *Knowl.-Based Syst.*, vol. 244, May 2022, Art. no. 108546.

[9] J. Li, Y. Wang, and J. McAuley, "Time interval aware self-attention for sequential recommendation," in *Proc. 13th Int. Conf. Web Search Data Mining*, Jan. 2020, pp. 322–330.

[10] W. Jiang, Z. A. Pardos, and Q. Wei, "Goal-based course recommendation," in *Proc. 9th Int. Conf. Learn. Anal. Knowl.*, Mar. 2019, pp. 36–45.

[11] J. Wang, H. Xie, F. L. Wang, L.-K. Lee, and O. T. S. Au, "Top-N personalized recommendation with graph neural networks in MOOCs," *Comput. Educ. Artif. Intell.*, vol. 2, Jan. 2021, Art. no. 100010.

[12] Y. Zhang and X. Chen, "Explainable recommendation: A survey and new perspectives," *Found. Trends Inf. Retr.*, vol. 14, no. 1, pp. 1–101, 2020.

[13] J. D. Chaudhuri, "Stimulating intrinsic motivation in millennial students: A new generation, a new approach," *Anatomical Sci. Educ.*, vol. 13, no. 2, pp. 250–271, Mar. 2020.

[14] J. D. Stolk, M. D. Gross, and Y. V. Zastavker, "Motivation, pedagogy, and gender: Examining the multifaceted and dynamic situational responses of women and men in college STEM courses," *Int. J. STEM Educ.*, vol. 8, no. 1, p. 35, Dec. 2021.

[15] S. Wan and Z. Niu, "A hybrid E-learning recommendation approach based on Learners' influence propagation," *IEEE Trans. Knowl. Data Eng.*, vol. 32, no. 5, pp. 827–840, May 2020.

[16] X. Tian and F. Liu, "Capacity tracing-enhanced course recommendation in MOOCs," *IEEE Trans. Learn. Technol.*, vol. 14, no. 3, pp. 313–321, Jun. 2021.

[17] J. Lin, Y. Li, and J. Lian, "A novel recommendation system via L0-regularized convex optimization," *Neural Comput. Appl.*, vol. 32, no. 6, pp. 1649–1663, Mar. 2020.

[18] Z. Y. Khan, Z. Niu, S. Sandiwarno, and R. Prince, "Deep learning techniques for rating prediction: A survey of the state-of-the-art," *Artif. Intell. Rev.*, vol. 54, no. 1, pp. 95–135, Jan. 2021.

[19] P. Symeonidis and D. Malakoudis, "Multi-modal matrix factorization with side information for recommending massive open online courses," *Expert Syst. Appl.*, vol. 118, pp. 261–271, Mar. 2019.

[20] J. Gong, S. Wang, J. Wang, W. Feng, H. Peng, J. Tang, and P. S. Yu, "Attentional graph convolutional networks for knowledge concept recommendation in MOOCs in a heterogeneous view," in *Proc. 43rd Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2020, pp. 79–88.

[21] D. Sheng, J. Yuan, Q. Xie, and L. Li, "ACMF: An attention collaborative extended matrix factorization based model for MOOC course service via a heterogeneous view," *Future Gener. Comput. Syst.*, vol. 126, pp. 211–224, Jan. 2022.

[22] Q. Shambour, "A deep learning based algorithm for multi-criteria recommender systems," *Knowl.-Based Syst.*, vol. 211, Jan. 2021, Art. no. 106545.

[23] W. Jiang and Z. A. Pardos, "Time slice imputation for personalized goal-based recommendation in higher education," in *Proc. 13th ACM Conf. Recommender Syst.*, Sep. 2019, pp. 506–510.

[24] X. Wang, W. Ma, L. Guo, H. Jiang, F. Liu, and C. Xu, "HGNN: Hyperedge-based graph neural network for MOOC course recommendation," *Inf. Process. Manage.*, vol. 59, no. 3, May 2022, Art. no. 102938.

[25] Y. Lin, S. Feng, F. Lin, W. Zeng, Y. Liu, and P. Wu, "Adaptive course recommendation in MOOCs," *Knowl.-Based Syst.*, vol. 224, Jul. 2021, Art. no. 107085.

[26] J. Zhang, B. Hao, B. Chen, C. Li, H. Chen, and J. Sun, "Hierarchical reinforcement learning for course recommendation in MOOCs," in *Proc. AAAI Conf. Artif. Intell.*, Dec. 2019, vol. 33, no. 1, pp. 435–442.

[27] H. Cai, T. T. Nguyen, Y. Li, V. W. Zheng, B. Chen, G. Cong, and X. Li, "Modeling marked temporal point process using multi-relation structure RNN," *Cognit. Comput.*, vol. 12, no. 3, pp. 499–512, May 2020.

[28] W. Liang and W. Zhang, "Learning social relations and spatio temporal trajectories for next check-in inference," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 4, pp. 1789–1799, Apr. 2023.

[29] D. Li, J. Liu, J. Jeon, S. Hong, T. Le, D. Lee, and N. Park, "Large-scale data-driven airline market influence maximization," in *Proc. 27th ACM SIGKDD Conf. Knowl. Discovery Data Mining*, Aug. 2021, pp. 914–924.

[30] A. G. Hawkes, "Spectra of some self-exciting and mutually exciting point processes," *Biometrika*, vol. 58, no. 1, p. 83, Apr. 1971.

[31] D. Wang, X. Zhang, Y. Wan, D. Yu, G. Xu, and S. Deng, "Modeling sequential listening behaviors with attentive temporal point process for next and next new music recommendation," *IEEE Trans. Multimedia*, vol. 24, pp. 4170–4182, 2022.

[32] D. Wang, X. Zhang, Z. Xiang, D. Yu, G. Xu, and S. Deng, "Sequential recommendation based on multivariate Hawkes process embedding with attention," *IEEE Trans. Cybern.*, vol. 52, no. 11, pp. 11893–11905, Nov. 2022.

[33] Y. Zhou, Y. Cao, Y. Shang, C. Zhou, S. Pan, Z. Lin, and Q. Li, "Explainable hyperbolic temporal point process for user-item interaction sequence generation," *ACM Trans. Inf. Syst.*, vol. 41, no. 4, pp. 1–26, Oct. 2023.

[34] M. Yao, S. Zhao, S. Sahebi, and R. Feyzi Behnagh, "Stimuli-sensitive Hawkes processes for personalized student procrastination modeling," in *Proc. Web Conf.*, Apr. 2021, pp. 1562–1573.

[35] H. Yuan, H. Yu, S. Gui, and S. Ji, "Explainability in graph neural networks: A taxonomic survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 5, pp. 5782–5799, May 2023.

[36] A. Heuillet, F. Couthouis, and N. Díaz-Rodríguez, "Explainability in deep reinforcement learning," *Knowl.-Based Syst.*, vol. 214, Feb. 2021, Art. no. 106685.

[37] G. Vilone and L. Longo, "Notions of explainability and evaluation approaches for explainable artificial intelligence," *Inf. Fusion*, vol. 76, pp. 89–106, Dec. 2021.

[38] G. Balloccu, L. Boratto, G. Fenu, and M. Marras, "Reinforcement recommendation reasoning through knowledge graphs for explanation path quality," *Knowl.-Based Syst.*, vol. 260, Jan. 2023, Art. no. 110098.

[39] J. Tan, S. Xu, Y. Ge, Y. Li, X. Chen, and Y. Zhang, "Counterfactual explainable recommendation," in *Proc. 30th ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2021, pp. 1784–1793.

[40] R. Yera, A. A. Alzahrani, and L. Martínez, "Exploring post-hoc agnostic models for explainable cooking recipe recommendations," *Knowl.-Based Syst.*, vol. 251, Sep. 2022, Art. no. 109216.

[41] J. Chen, J. Yu, W. Lu, Y. Qian, and P. Li, "IR-rec: An interpretive rules-guided recommendation over knowledge graph," *Inf. Sci.*, vol. 563, pp. 326–341, Jul. 2021.

[42] R. Shimizu, M. Matsutani, and M. Goto, "An explainable recommendation framework based on an improved knowledge graph attention network with massive volumes of side information," *Knowl.-Based Syst.*, vol. 239, Mar. 2022, Art. no. 107970.

[43] R. Lemonnier, K. Scaman, and A. Kalogeratos, "Multivariate Hawkes processes for large-scale inference," in *Proc. AAAI Conf. Artif. Intell.*, 2017, vol. 31, no. 1, pp. 11–13.

[44] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 30, 2017, pp. 1–16.

[45] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian personalized ranking from implicit feedback," 2012, *arXiv:1205.2618*.

[46] B. Hidasi, A. Karatzoglou, L. Baltrunas, and D. Tikk, "Session-based recommendations with recurrent neural networks," 2015, *arXiv:1511.06939*.

[47] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, and J. Leskovec, "Graph convolutional neural networks for web-scale recommender systems," in *Proc. 24th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Jul. 2018, pp. 974–983.

[48] X. He, K. Deng, X. Wang, Y. Li, Y. Zhang, and M. Wang, "LightGCN: Simplifying and powering graph convolution network for recommendation," in *Proc. 43rd Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jul. 2020, pp. 639–648.

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