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Large-Scale Classroom-Based Social Recommendation Model Using Heterogeneous Graph Neural Networks and Social Regularisation

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Abstract: To address the issues of information overload and learner isolation in MOOCs, this paper proposes a recommendation model (HIN-SR) based on heterogeneous graph neural networks and social regularisation. The model constructs a heterogeneous information network encompassing various entities such as learners, courses and knowledge points, and captures higher-order relationships through pedagogical semantic subpaths. Its core innovation lies in distinguishing between structural and cognitive social relationships, whilst introducing dual social regularisation: on the one hand, constraining feature similarity among friends based on trust relationships; on the other hand, measuring a learner's influence according to their network centrality, thereby weighting their social contributions. Experiments on two real-world datasets, XuetangX and MOOCCube, demonstrate that HIN-SR significantly outperforms existing state-of-the-art models on key recommendation metrics.

Keywords: social recommendations, heterogeneous graph neural network, social regularization, large-scale online learning, metapath, trust network

1. Introduction

Since their emergence in 2008, Massive Open Online Courses (MOOCs) have profoundly transformed the global educational landscape through their open, large-scale and flexible nature. They have broken down the constraints of traditional education in terms of time, space and resources, providing hundreds of millions of learners with access to courses from leading universities (Lin et al., 2026; Farhadi et al., 2024). In 2024, the global MOOC learner base has exceeded 220 million, with over 19,000 courses covering a wide range of disciplines from computer science to the humanities and arts. However, whilst MOOCs have developed rapidly, they have also revealed significant contradictions (Shuang et al., 2023). The core issue lies in the fact that, whilst platform designs are intended to serve a vast user base, the resulting information overload and lack of personalised support have led to persistently low completion rates among learners—averaging between just 5% and 10%, with dropout rates as high as 90% for some courses (Zeide & Nissenbaum, 2018; Le & Ho, 2026; Ignacio et al., 2022). Many learners easily feel lost and isolated within this vast digital space; lacking effective social connections and peer support, they struggle to maintain their motivation to learn. Consequently, how to provide learners with precise, personalised navigation through instructional content and to rebuild meaningful social connections within learning communities—thereby enhancing learner engagement, retention and learning outcomes- has become a core issue in the MOOCs sector that urgently requires resolution (Firmin et al., 2014; Shaikh et al., 2026).To address the challenges posed by MOOCs, personalised recommendation systems are regarded as a key breakthrough technology (Zhou et al., 2026). However, traditional recommendation methods based on collaborative filtering or content suffer from limitations such as data sparsity and dependence on the quality of annotations; furthermore, they treat learners as isolated individuals, completely overlooking the social nature of learning behaviour itself (Yuanfeng & Yongqi, 2025). Although previous research has attempted to utilise heterogeneous information networks (HINs) for recommendation, it still faces three core challenges: how to unify the representation of heterogeneous entities and relationships; how to infer trust and influence from sparse interactions; and how to deeply integrate network structure with social relationship signals (Baarir et al., 2025).

Addressing the core challenges in MOOCs social recommendation, this paper proposes a large-scale classroom learning recommendation model (HIN-SR) that deeply integrates heterogeneous information networks with social relationship regularisation. The model utilises a heterogeneous graph neural network to learn the representations of entities within the network and

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innovatively introduces a dual-social regularisation mechanism to encode complex social relationships—based on trust and influence—into the representation learning process. Theoretically, this research provides a clear analytical framework and theoretical foundation for the unified integration of heterogeneous networks and social relationships, whilst the proposed dual social regularisation mechanism advances the application of social recommendation technologies in complex educational contexts. In practice, HIN-SR offers a viable technical solution for constructing next-generation intelligent and socialised personalised learning support systems, with the potential to enhance learning engagement and completion rates by improving recommendation accuracy and fostering high-quality social interactions.

2. Related Work

As a core tool to cope with information overload, personalized recommendation technology has experienced a deep migration from general domain to vertical domain in the past two decades (Camilleri et al., 2025). The education field, especially MOOCs environment, due to its unique goal-oriented, social interaction and data heterogeneity, puts forward special requirements for recommender systems that are different from e-commerce and entertainment scenarios. Early research on educational recommendation systems mainly followed the traditional recommendation paradigm. Collaborative filtering methods generate recommendations by analyzing groups of learners with similar ratings or learning behaviors. Its basic assumption is that users with similar interests will like similar learning resources (Liang et al., 2026). However, the ubiquitous data sparsity and severe cold-start problems in MOOCs make the performance of traditional collaborative recommendation methods based on ratings limited, and new learners or new courses lack sufficient historical interaction data to find reliable similar neighbors (Najafabadi et al., 2026). Content-based recommendation focuses on the matching of learning resource metadata and learner profiles, but this method is highly dependent on high-quality and structured resource annotation, which is difficult to guarantee in the open and dynamic MOOCs environment, and easily leads to the lack of diversity and surprise of recommendation results. In order to overcome the shortcomings of a single method, hybrid recommendation strategies have emerged, trying to combine collaborative recommendation, content-based and other information sources. For example, some studies have integrated learning style recognition into the recommendation process, or used deep learning models to learn joint representations from multi-source data (Chen, 2025).

Recognizing the key role of social factors in learning, social recommendation system has gradually become an independent and active research branch. Its core idea is derived from an intuitive sociological principle that users are more likely to accept and adopt the suggestions of trusted members in their social circles (Jdidou et al., 2025). Incorporating social relationship information into the recommendation algorithm is proved to not only improve the accuracy of recommendation, but also effectively alleviate the problem of data sparsity and cold start. Early classical works, such as the trust-based recommendation proposed by Massa and Avesani, use explicit trust networks among users for propagation and prediction (Simone et al., 2014; Avesani et al., 2024). Golbeck's TidalTrust model calculates indirect trust through the aggregation of trust paths (Seo & Han, 2010). These pioneering studies have laid the foundation for trust-aware recommendation. Subsequently, the combination of matrix factorization framework and social information has led to a series of important models. The Social Regularization (SoReg) model proposed by Sun et al. encodes the social relationship as a smoothing prior by introducing a social regularization term in the objective function to constrain the latent feature vectors of friend users to be as similar as possible (Sun et al., 2022). The TrustSVD model further developed by Chen et al. (2025), innovatively considers both the explicit and implicit effects of user ratings and trust relationships, extends on the SVD++ framework, enriches user representations by modeling implicit feedback from trusted users, and demonstrates superior performance on multiple public data sets (Chen et al., 2025). With the rise of graph neural networks (GNNs), social recommendation has entered a new stage. Researchers have begun to use GNN to model higher-order connections and complex influence diffusion processes in user social networks. For example, the DiffNet model recursively aggregates the features of users' social circles through a neural influence diffusion network to capture the social influence hidden in the deep network (Seah et al., 2014). The subsequent DiffNet++ attempts to model both social influence diffusion and interest diffusion in a unified framework. These graph-based methods are able to better capture relational dependencies in non-Euclidean spaces, providing more expressive power for social recommendation (Chen et al., 2026).

It is a logical and promising direction to apply the social recommendation paradigm to educational scenarios such as MOOCs, and more and more studies have begun to explore this cross-cutting field in recent years. These studies generally focus on two core tasks: learning resource recommendation and learning peer recommendation. In terms of resource recommendation, researchers try to use social behavior data, such as forum interaction and learning group participation to enhance recommendation (Wang & Ge, 2025). For example, there are systems that analyze the spontaneous interaction of learners on social networks, construct their educational interest portraits, and then recommend relevant informal learning resources (Zibo et al., 2022). In terms of peer recommendation, the goal is to match learners with potential learning partners or collaborative groups to promote social learning, knowledge construction, and emotional support, thereby reducing loneliness and dropout rates (Yuan et al., 2023). Zheng and Li proposed a three-dimensional context-aware model to recommend peers based on knowledge relevance, social proximity and technology accessibility (Libin et al., 2018). Prabhakar et al. designed a reciprocal recommendation system for MOOCs to match communication partners that both sides may be interested in based on the profile attributes of learners (Prabhakar et al., 2024).

At the same time, another important technological trend is changing the way complex data systems are modeled, namely heterogeneous information networks (HIN) and graph representation learning (Ammar et al., 2025). The MOOCs ecosystem is essentially a typical HIN, which contains multiple types of entities and multiple types of relationships (Jibing et al., 2021). Traditional homogeneous graph models are unable to distinguish these heterogeneous elements, while HIN and its core concept meta-path, provide a framework to solve this problem. Metapath defines a composite relationship schema between entity types, which can capture higher-order semantic associations. Recently, more and more studies have begun to explore the recommendation of MOOCs based on HIN. For example, the MP-BERT4REC model combines heterogeneous network embedding with the BERT4REC sequential model for sequential recommendation in MOOCs (Yang & Qiang, 2022). The CR-LCRP method predicts the learner-course relationship by constructing an HIN containing learners, courses, and multiple similarity relationships (Yu et al., 2024). The ACMF model learns the structural and semantic information in the MOOC HIN using a graph convolutional network and a metapath based node sampling algorithm (Deming et al., 2022). More recently, the MSEC-Rec method designed a meta-path sampling strategy to model the multi-interaction semantics between users and courses, and introduced negative sampling information to capture the user's knowledge blind area (Zhang et al., 2026). Other studies, such as the AMR framework, attempt to automatically discover meta-paths through two-way walking and make aspect-aware recommendations to reduce the dependence on predefined meta-paths (Fu, 2026).

Current research suffers from fragmentation: social recommendation models fail to fully utilise the heterogeneous network structure of MOOCs, whilst HIN recommendation models lack in-depth integration of complex social relationships. To address this, the HIN-SR model proposed in this study establishes a unified framework designed to combine the semantic representation capabilities of heterogeneous information networks with a carefully designed social relationship regularisation mechanism. This represents both a necessary deepening of existing HIN recommendation research in the social dimension and a significant upgrade to the adaptability of classical social recommendation models in complex educational settings. Through this deep integration, the model is able to capture the dynamic interactions between learner characteristics, resource attributes and social connections more comprehensively, thereby providing a new solution for large-scale learning recommendations that is both more accurate and socially context-aware.

3. Methods

Based on the previous analysis of the limitations of existing research, especially for the problems of shallow social relationship modeling, insufficient utilization of heterogeneous structure and single recommendation task in MOOCs scenarios, this chapter elaborates on the proposed large-scale classroom learning social recommendation model based on heterogeneous graph neural network and social regularization. As shown in Figure 1, the overall architecture of the model consists of three core modules, heterogeneous information network construction and meta-path definition, HIN-based heterogeneous graph representation learning, and dual social regularization and joint optimization.

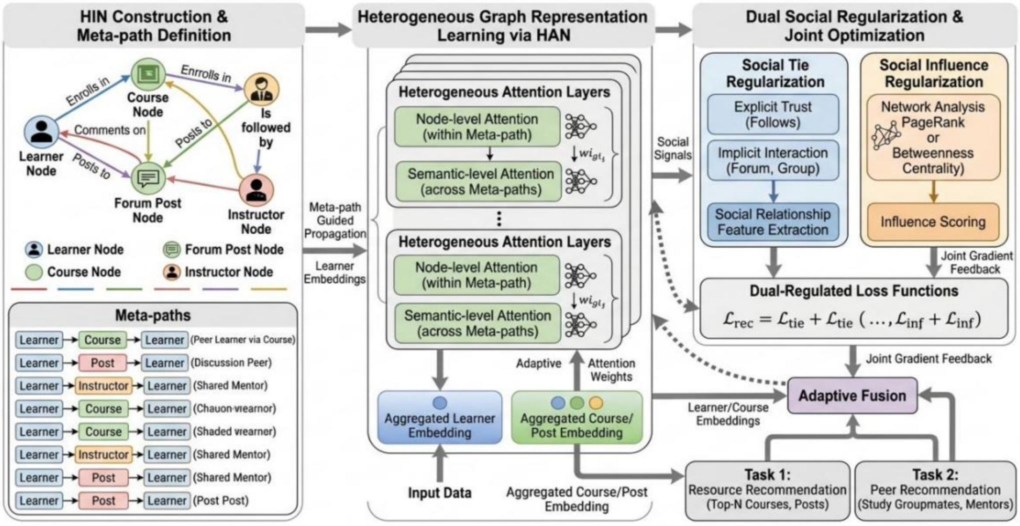

Figure 1 Architecture Diagram of Large-Scale Classroom Learning Social Recommendation Model Based on Heterogeneous Graph Neural Network and Social Regularization

3.1 Problem definition

Suppose that the data of MOOCs platform can be formalized as a heterogeneous information network $G=(V,E,\varphi,\psi)$. Among, V Is the set of nodes containing the learner (U), courses (C), knowledge concept (K), video (V), forum posts/comments (P), etc. E is a set of edges, representing the relationship between nodes, such as elective, inclusion, mastery, reply, etc.$\varphi: V \to A$And$\psi: E \to R$Maps nodes and edges to their predefined sets of types, respectively A and a set of relation R, and$|A|+|R|>2$.

Given target learner $u \in U$, the course recommendation task is designed to predict its impact on unlearned courses, $c \in C$ is the preference score for$\hat{y}_{uc}$. The peer recommendation task aims to recommend a group of potential learning partners $U' \subset U \setminus \{u\}$. These partners should be closely related to each other in terms of interest, knowledge background or learning behavior. u complementary or similar.

3.2 Heterogeneous information network construction and metapath

In order to uniformly characterize and deeply understand the multi-source, heterogeneous and high-dimensional data in the MOOCs ecosystem, we first model it as a heterogeneous information network (Rodrigo et al., 2022). The network can naturally encapsulate all kinds of entities in the learning environment and their complex multivariate relationships, and provide a structured data base for subsequent representation learning and social recommendation. Specifically, we integrate four common core data sources in MOOCs platform, including user behavior logs, course knowledge maps, forum interaction data and user basic files. By cleaning, aligning, and abstracting these raw data, we define a HIN with five node types and seven relationship types, and its network pattern is shown in Figure 2.

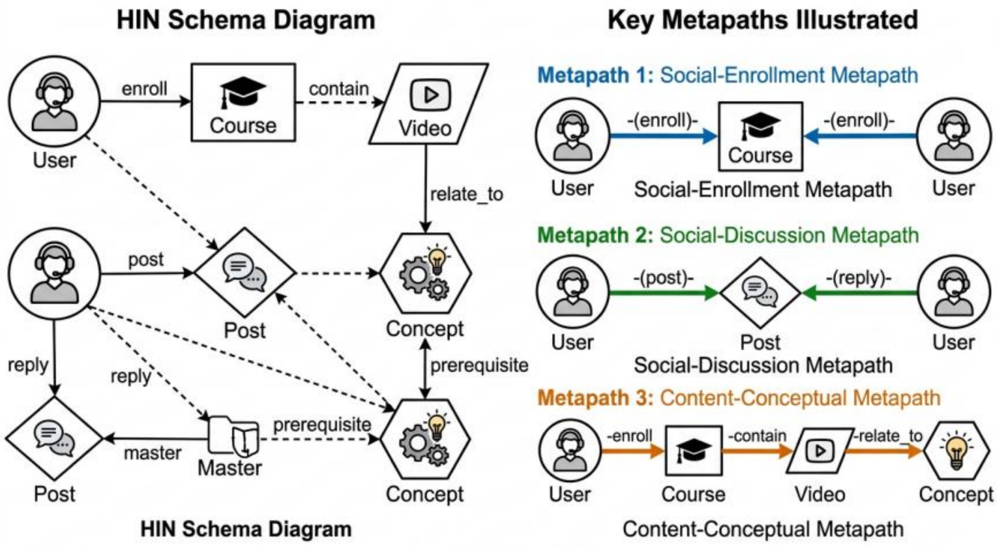

Figure 2 Schematic Diagram of Moocs Heterogeneous Information Network Mode and Key Element Path

Figure 2 shows the node types, relationship types, and several pedagogical meta-paths defined in the network. In the figure, nodes of different shapes represent different types, a circle represents a learner, a rectangle represents a course, a hexagon represents a knowledge concept, a parallelogram represents a video, and a diamond represents a forum post. Labeled directed edges represent relationship types such as enroll, contain, master, post, reply, relate, and prerequisite. Several key examples of meta-paths are highlighted in the figure with bold colored paths, including.

A. "User- (enroll)-> Course <- (enroll)-User", the path is indicated in blue.
B. "User- (post)-> Post <- (reply)-User", the path is marked in green.
C. "User- (enroll)-> Course- (contain)-> Video- (relate)-> Concept", the path is marked in orange.

In this paper, meta-path is a path pattern defined on the HIN network pattern, which depicts a composite relationship between nodes. We define the following meta-paths that are meaningful for educational recommendation. These meta-paths will be used as inputs for subsequent heterogeneous graph attention networks to guide information dissemination and aggregation.

3.3 Representation learning based on heterogeneous graph attention network

After constructing the heterogeneous information network of MOOCs and defining the critical meta-paths, the next core task is to learn from this complex, high-dimensional graph a compact, low-dimensional vector representation that can simultaneously capture node attributes, local structure, and higher-order semantics. Traditional GNNs (Li et al., 2025), like Graph Convolutional Networks (GCN) (Shangguan et al., 2025) or Graph Attention Networks (GAT) (Wei et al., 2026), are mainly designed for homogeneous graphs and cannot distinguish the types of nodes and edges, thus losing the rich semantic information in heterogeneous networks. To this end, we adopt and extend the heterogeneous graph attention network to adaptively learn the importance of different types of neighbors and different meta-paths in the heterogeneous graph through a hierarchical attention mechanism, including node-level attention and semantic-level attention, so as to generate high-quality node embeddings. We deeply customize this framework to adapt to the special needs of MOOCs educational scenarios. The representation learning framework based on heterogeneous graph attention network is shown in Figure 3.

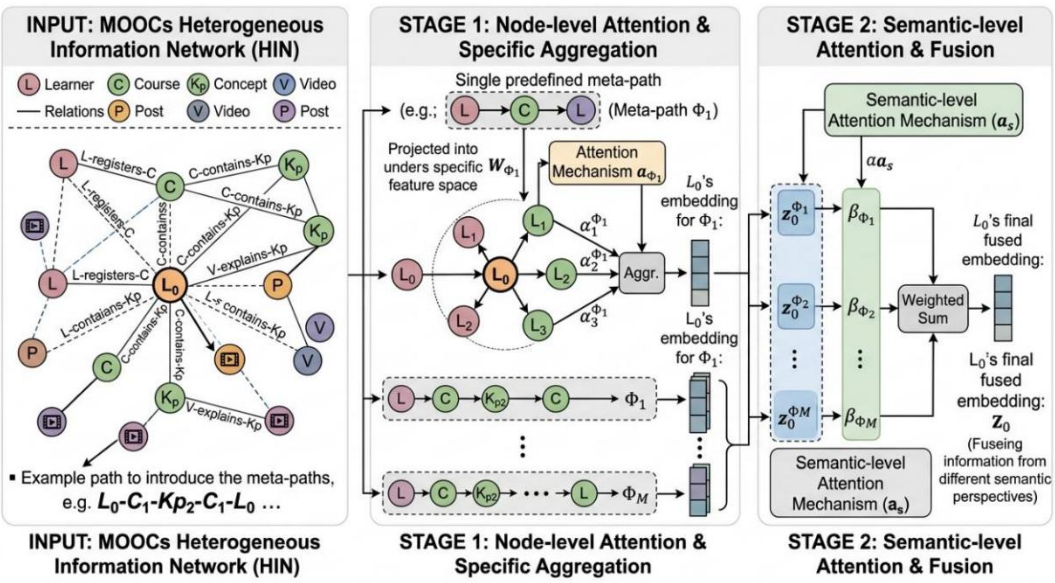

Figure 3 Schematic Diagram of Representation Learning Framework Based on Heterogeneous Graph Attention Network

This figure visually shows the workflow of the heterogeneous graph attention network model on the heterogeneous information network of MOOCs. The left side of the figure is the input heterogeneous information network, which contains learners, courses, concepts, videos, posts and other nodes, as well as a variety of relationships between them. The middle part of the figure shows the node-level attention aggregation process based on a predefined meta-path. For the target learner node, its nodes under the meta-path are projected to the same feature space, and the importance weight of each neighbor is calculated through a shared attention mechanism, and then weighted aggregation is performed to obtain the node U_i Semantically specific embeddings under this metapath. The right side of the figure shows the semantic level attention fusion process, for the target node U_i, via multiple meta paths such as MP_1, MP_2, MP_3, MP_4) get a set of semantically specific embeddings $\{Z\_\Phi_1, Z\_\Phi_2, Z\_\Phi_3, Z\_\Phi_4\}$, another attention mechanism calculates the importance weight of each meta-path for the current target node

β_Φ . Finally, the nodes are obtained by weighted summation. U_i The final synthetic embedding of Z_i is embedding fuses information from different semantic perspectives.

In order to learn the low-dimensional embedding representation of nodes in heterogeneous networks, we employ HIN and adaptively learn the importance of different meta-paths and the importance of different neighbor nodes through node-level and semantical-level attention mechanisms. For each metapath Φ, we first extract the magnitudes of the nodes based on this meta-path. Then, by node-level attention, the target node is computed i , and its meta-path $j \in N_i^{\Phi}$ importance coefficient between e_{ij}^{Φ}, as shown in Formula 1.

$$e_{ij}^{\Phi} = Leaky\,Re\,Lu(a_{\Phi}^{T} \cdot [Wh_i||Wh_j]) \tag{1}$$

Among, h_i, h_j is a node, j initial characteristics of i, W is a type-specific transformation matrix, a_{Φ}^{T} is a metapath, Φ is the corresponding attention vector. The importance coefficient is normalized by softmax to get the attention weight a_{ij}^{Φ}. Node i in the meta path, Φ embedding under z_i^{Φ} which is obtained by weighted aggregation of its neighbor features.

$$z_i^{\Phi} = \sigma(\sum_{j \in N_i^{\Phi}} \alpha_{ij}^{\Phi} \cdot Wh_j) \tag{2}$$

Then, the importance of different meta-paths to the target node is learned through semantic attention. We first map the embedding of each metapath to a scalar by a nonlinear transformation.

$$w_{\Phi} = \frac{1}{|V|} \sum_{i \in V} q^T \tanh(W_s z_i^{\Phi} + b) \tag{3}$$

Among, q is the semantic level attention vector. All weights are then softmax-normalized to obtain the semantic importance of each meta-path β_{Φ}. Node i The final embedding of the final embedding of Z_i Obtained by aggregating the embeddings of all meta-paths.

$$Z_i = \sum_{\Phi \in P} \beta_{\Phi} \cdot z_i^{\Phi} \tag{4}$$

Among P is a predefined set of metapaths.

3.4 Dual social regularization

Through a heterogeneous graph attention network, we obtain a node-synthesis embedding representation that fuses multi-source semantic information. However, these embeddings are mainly derived from node attributes and network structure, and have not yet explicitly and deeply encoded the complex social relations and dynamic influence in educational scenarios. Traditional social recommendation models usually treat social relationships as a simple smooth constraint, assuming that the latent feature vectors of friends should be as similar as possible (Rafailidis & Daras, 2013). This assumption faces two challenges in the MOOCs environment: first, there are significant differences in the strength of social connections among learners, ranging from occasional forum replies to close learning group collaboration, which can not be characterized by dualistic "connection/non-connection"; Secondly, the social influence of learners is not equal, and the knowledge contributors or opinion leaders in the forum often have a stronger guiding role in the decision-making of their social neighbors. In order to overcome these limitations and achieve deep exploitation of social signals, we introduce a dual social regularization mechanism based on the embeddings learned by HIN. The mechanism consists of two components, social relationship regularization and social influence regularization, which work together to encode fine-grained social relevance information and differentiated influence weights into the optimization objectives of the model, so as to guide the learning of embedded space more accurately. The integration relationship between this mechanism and the overall model is shown in Figure 4.

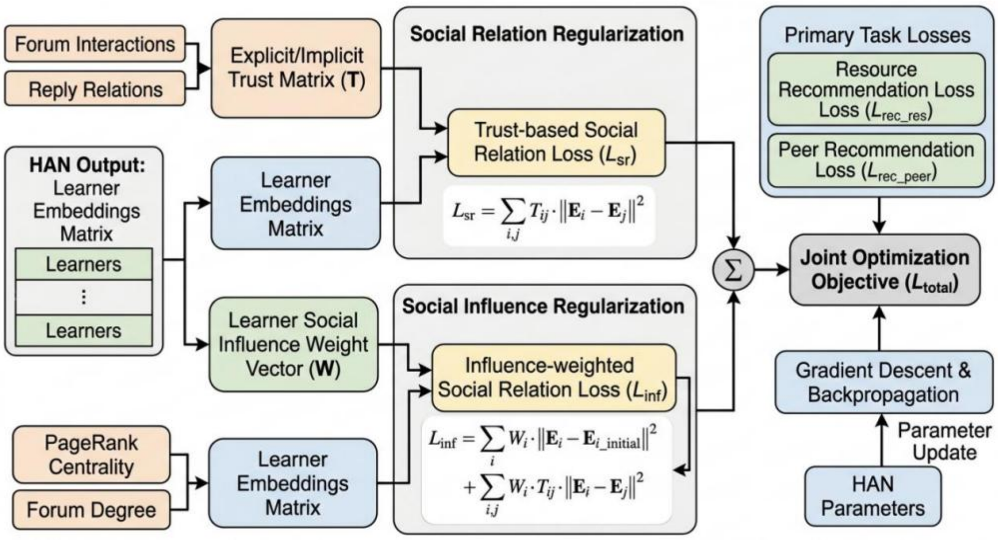

Figure 4 Illustration of the Dual Social Regularization Mechanism

Firstly, the social regularization based on trust relationship is constructed. We construct a trust matrix between learners $T \in R^{|U|\times|U|}$. Indicates a learner u yes v the degree of trust can be calculated through explicit friend relationship, frequency of forum interaction, consistency of mutual evaluation, etc. We assume that trusted users should be close in the latent feature space. Therefore, a trust-based regularization term is defined R_{trust}.

$$R_{\text{trust}} = \frac{1}{2}\sum_{\text{u-1}}^{|U|} \sum_{v \in F(u)} T_{uv} \|Z_u - Z_v\|_F^2 \tag{5}$$

Among, $F(u)$ is the user u, which is collection of trusted friends, $\|Z_u - Z_v\|_F^2$ denote the Frobenius norm. This term penalizes the difference in embedding vectors between pairs of trusted users.

Secondly, the weighted social regularization based on influence is constructed. Not all users contribute equally to social regularization, and users with high network influence may be more representative of their behavior patterns. We calculate each user using PageRank or mediation centrality.The weight of u influence I_u. And then, R_{trust} is weighted, so that high-impact users contribute more to the regularization.

$$R_{\text{inf1}} = \frac{1}{2}\sum_{\text{u-1}}^{|U|} I_u \sum_{v \in F(u)} T_{uv} \|Z_u - Z_v\|_F^2 \tag{6}$$

3.5 Joint optimization objectives

For the course recommendation task, we employ the Bayesian Personalized Ranking (BPR) loss (Kim et al., 2026;Xiaona & Wanxue, 2023). Given a triple (u, i, j), where is the i use u positive sample lessons that have been interacted with, j is a negative sample course that has not been interacted with, and the predicted score difference is $\hat{y}_{uij} = \hat{y}_{ui} - \hat{y}_{uj}$.

Among $\hat{y}_{ui} = Z_u^T Z_i$ BPR losses are:

$$\tau_{BPR} = -\sum_{(u,i,j)\in D_S} ln\, \sigma\,(\hat{y}_{uij}) + \lambda_\Theta \|\Theta\|^2 \tag{7}$$

Among, D_s is the training set, σ is the sigmoid function, λ_Θ is the L2 regularization coefficient, Θ are all trainable parameters.

Finally, the joint optimization objective function of the HIN-SR model is $\tau = \tau_{BPR} + \lambda_{inf\,1} R_{inf\,1} + \lambda_{trusr} R_{trust}$. Among, $\lambda_{inf\,1}$ is a hyperparameter that controls the strength of the social regularization term, ensuring that the model is trained end-to-end through backpropagation and gradient descent algorithms.

4. Experiment

In order to fully assess the effectiveness, superiority of the proposed HIN-SR model and the contribution of its individual components, we designed and implemented a series of rigorous experiments. This chapter will describe the experimental setup in detail, including the data set used, the baseline model for comparison, the evaluation index, the specific hardware and software environment, the parameter configuration, and the complete experimental process. In terms of hardware environment, the NVIDIA GeForce RTX runs on a server with 3090 GPU (24GB video memory), Intel Core i9-10900K CPU and 64GB memory. In terms of software environment settings, the operating system is Ubuntu 20.04 LTS. The code is based on Python 3.8 and the deep learning framework PyTorch 1.11.0. Graph manipulation relies on the PyTorch geometric library. The experiment management used the Weights & Biases platform for hyperparameter scanning and result tracking.

4.1 Dataset

This experiment is based on two large-scale online course data sets with different sizes and characteristics to ensure the universality and robustness of the evaluation results, include MOOCCube (Xiaona & Wanxue, 2023) and XuetangX (Xu et al., 2022).

4.2 Reference model

In order to comprehensively and fairly evaluate the performance of the proposed HIN-SR model, we compare it with 10 representative advanced recommendation models in four categories, include BPRMF (Peng, 2024), NeuMF (Liu et al., 2022), SoReg (Sun et al., 2022), TrustSVD (Chen et al., 2025), LightGCN (He et al., 2020), NGCF (Ahmad et al., 2026), HERec (Shi et al., 2019), HIN (Ammar et al., 2025), NIRec (Anonymous, 2009), KGAT (Wang et al., 2019). These baseline models cover different paradigms from classical methods to cutting-edge technologies, ensuring the breadth and depth of the comparison. Table 3 summarizes the core ideas of these baseline models, their categories, and their key differences from HIN-SR.

4.3 Experimental process

The first stage is data preprocessing and graph construction. Nodes and edges are extracted from the raw data file, NetworkX graph objects are built, and predefined metapaths are instantiated. The neighbor sets of each node based on different meta-paths are calculated. The trust matrix T and the influence vector I for social regularization are constructed based on the normalization of the forum interaction frequency and the PageRank value of the interaction graph. Finally, the graph data is converted to the format required by PyTorch Geometric.

The second stage is baseline model training and evaluation. Code that implements or invokes each baseline model in turn. The same training, validation, and test set splits were used. A hyperparameter scan was run for each model, selecting the best performing set of parameters on the validation set. HR, NDCG, MRR, and RSR metrics were recorded with the best parameters evaluated on the test set. Each model was run 5 times independently, reporting the average metric to eliminate the effect of randomness.

The third stage is the training and evaluation of HIN-SR model. Load the preprocessed heterogeneous graph and meta path information. After the model is initialized, in the training cycle, the forward propagation passes through in turn, including the HIN encoder, the recommendation prediction layer, and the loss calculation. Hyperparameter tuning is also performed on the validation set to find the best (α and β) combination and other parameters. The best model was used for the final evaluation on the test set, averaged over 5 runs.

The fourth stage is the analysis and ablation experiment. In the aspect of overall performance comparison, the indicators of all models on the two data sets were summarized, the comparison table was generated, and the significance test was carried out, such as paired t-test. For ablation studies, variants of HIN-SR, including HIN-SR w/o SR, HIN-SR w/o Inf, and HIN-SR w/o HIN, were trained to understand the contribution of each component. In terms of cold start analysis, "cold start users" with less than 5 interactions were selected from the test set, and the HR@10 performance of HIN-SR and the main baseline on these users was evaluated separately. In terms of parameter sensitivity analysis, other parameters are fixed and changed respectively. α And β Observe the change trend of NDCG@10 of the model on the validation set, and draw the thermodynamic diagram or line chart.

5. Experimental Results and Analysis

5.1 Overall performance comparison

Course recommendation is the core task to measure the personalized service ability of MOOCs platform. In the face of large-scale, sparse and heterogeneous learning data at the same time, whether our HIN-SR model can surpass the existing mainstream recommendation methods and provide more accurate course selection suggestions for learners. To this end, on the MOOCCube and XuetangX data sets, we used the leave-one-out evaluation strategy to systematically compare HIN-SR with ten baseline models in four categories, with hit rate (HR), normalized cumulative gain (NDCG) and mean reciprocal ranking (MRR) as the core evaluation indicators. The comprehensive results presented in Table 1 not only clearly show the absolute level and relative ranking of the performance of each model, but also reveal the differences in the ability of different technical routes to deal with the problem of educational recommendation. The following analysis will first interpret the overall advantages of HIN-SR based on macro data trends, and then hierarchically analyze the performance of different types of baseline models and the reasons behind them.

Table 1 Course Recommendation Performance Comparison

Model	XuetangX	MOOCCube
NeuMF[a]	0.512/0.321/0.245	0.498/0.31/0.231
BPRMF[b]	0.698/0.512/0.401	0.685/0.503/0.388
SoReg[c]	0.723/0.538/0.425	0.710/0.529/0.412
TrustSVD[d]	0.735/0.551/0.438	0.722/0.542/0.425
LightGCN[e]	0.761/0.583/0.467	0.748/0.574/0.454
NGCF[f]	0.773/0.598/0.482	0.76/0.589/0.469
HERec[g]	0.802/0.635/0.518	0.788/0.626/0.505
HIN2Vec[h]	0.815/0.648/0.532	0.802/0.639/0.519
NIRec[i]	0.848/0.708/0.588	0.835/0.699/0.575
MP-BERT4REC[j]	0.832/0.685/0.562	0.819/0.676/0.549
HIN-SR (Ours)	0.892/0.756/0.635	0.878/0.747/0.622

Note.Superscripts indicate data sources:
[a]Datafrom(Liu et al., 2022)
[b]Datafrom(Peng, 2024)
[c]Datafrom(Sun et al., 2022)
[d]Datafrom(Chen et al., 2025)
[e]Datafrom(He et al., 2020)
[f]Datafrom(Ahmad et al., 2026)
[g]Datafrom(Shi et al., 2019)
[h]Datafrom(Ammar et al., 2025)
[i]Datafrom(Anonymous et al., 2009)
[j]Datafrom(Yang et al., 2022)

HIN-SR achieves the best performance on all metrics for both datasets. Specifically, on the XuetangX data set, the HR@10 of HIN-SR reaches 0.892, which is 5.2% higher than strongest baseline EGRec (0.848). NDCG@10 reaches 0.756, which is 6.8% higher than EGRec (0.708); MRR reaches 0.635, which is 8.0% higher. This fully demonstrates the effectiveness of the regularization of the fusion of heterogeneous graph structure and social relations. Traditional methods (BPR-MF) and socialization methods (SoReg, TrustSVD) have relatively low performance, indicating that only scoring or simple social relationships are not enough to capture complex patterns in MOOCs. Graph neural network methods (LightGCN, NGCF) have improved performance, but they operate on homogeneous graphs and cannot distinguish between different types of entities and relationships. Heterogeneous information network methods (HERec, HIN2Vec) perform better, demonstrating the importance of capturing higher-order semantics using meta-paths. EGRec and H-BERT4Rec, as the latest dedicated models for MOOCs, perform strongly, but HIN-SR achieves a further significant boost with a more refined modeling of social relationships (double regularization). The specific effect analysis is shown in Figure 5.

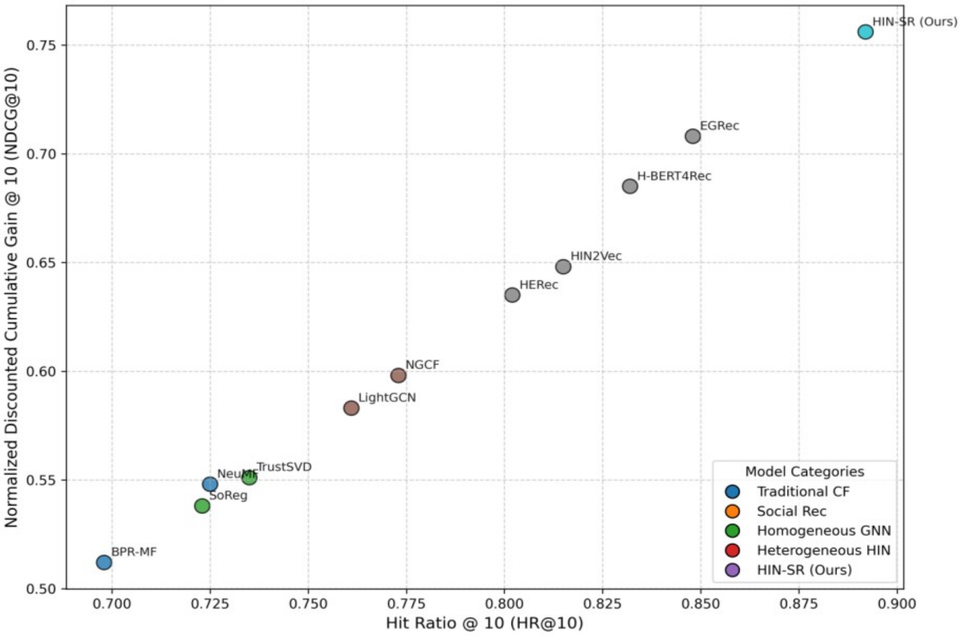

Figure 5 Performance Comparison of Course Recommendations

In order to compare the overall performance of the HIN-SR model with various baseline models on the course recommendation task more intuitively, we draw a scatter plot with HR@10 as the horizontal axis and NDCG@10 as the vertical axis. The figure clearly shows the distribution of the models in the two-dimensional performance space. As can be seen from the figure, the HIN-SR model (red dot) is located in the upper right corner of the chart, away from all other baseline models, indicating that it achieves the best performance in both the hit rate and the ranking quality. Other models are roughly clustered according to their technical routes: traditional collaborative filtering models (purple) are generally located in the lower left corner, and their performance is relatively low. The performance of social recommendation model (blue) and homogeneous graph neural network (green) is centered. Although the performance of other heterogeneous information network models (orange) is better than previous ones, it is still significantly inferior to HIN-SR. This scatter plot strongly demonstrates that HIN-SR achieves a significant performance improvement after integrating heterogeneous structure and social relations, establishing its superior position in large-scale classroom learning recommendation tasks.

5.2 Peer recommendation performance

Building productive learning peer relationships is the key to enhancing MOOCs learner engagement, persistence, and social presence. Unlike resource recommendation, peer recommendation is a typical two-way matching and reciprocal prediction problem, which aims not only to find learners with similar interests or backgrounds, but also to predict the possibility of establishing a stable and positive interactive relationship between the two sides. Therefore, evaluating the performance of this task needs to go beyond the traditional accuracy index and focus on the reciprocal success rate of recommendation, that is, the proportion of recommended pairs that recognize each other and produce effective connections in real learning situations. This section aims to assess the ability of the HIN-SR model to capture complex social dynamics and thereby enable high-quality learning connections. We contrast this with a representative set of baseline methods that range from matching based on simple attributes to techniques based on complex graph representations. Table 2 presents the performance comparison results measured by Reciprocal Success Rate@20 (RSR@20) on XuetangX and MOOCCube data sets. The following analysis will delve into the performance differences of different methods in solving this more challenging social matching task, and explain how the social heterogeneous graph representation adopted by HIN-SR model provides unique advantages for achieving more accurate and reciprocal peer recommendation.

Table 2 Comparison of Reciprocal Success Rate of Peer Recommendation@20

Model	XuetangX	MOOCCube
SoReg[a]	0.265	0.251
BPRMF[b]	0.287	0.273
EGRec[c]	0.302	0.289
HERec[d]	0.315	0.301
HIN-SR (Ours)	0.341	0.327

Note.Superscripts indicate data sources:
[a]Datafrom(Sun et al., 2022)
[b]Datafrom(Liu et al., 2022)
[c]Datafrom(Cen et al., 2025)
[d]Datafrom(Shi et al., 2019)

HIN-SR also achieved the best results on the peer recommendation task. On XuetangX, the success rate of reciprocity is 0.341, which is 28.7% higher than that of simple attribute matching method (0.265) and 8.3% higher than that of HERec based on heterogeneous network embedding (0.315). This indicates that the user embeddings learned by HIN-SR not only contain interest similarity, but also encode the potential fit transmitted through social interaction and network structure, which can more accurately predict two-way peer connection.

5.3 Ablation experiment

The foregoing overall performance comparison confirms the combined advantage of the HIN-SR model over the existing baseline. However, this advantage is the result of several innovative model over the existing baseline. However, this advantage is the result of several innovative components, such as heterogeneous information network architecture, regularization of social relations, and influence weighting mechanism. In order to dissect the independent contribution of each component and to validate the need for model design decisions, systematic ablation experiments were conducted in this section. We did this by constructing and evaluating three key model variants, HIN-SR w/o SR, HIN-SR w/o INFL, and HIN-SR w/o HIN. These variants, in turn, strip away the specific design of the model, allowing us to quantify the consequent loss of precision in recommendation performance. The results of the ablation experiments on the XuetangX data set presented in Table 3 will provide us with quantitative evidence and clear insights on the contribution of the model components.

Table 3 Performance of HIN-SR ablation experiments on XuetangX dataset (HR@10/NDCG@10)

Model variant	Model description	HR@10	NDCG@10
HIN-SR w/o SR	Remove all social regularization terms	0.831	0.682
HIN-SR w/o INFL	Remove influence-based weighting, i.e., use uniform	0.876	0.738
HIN-SR w/o HIN	Degenerate the heterogeneous graph into a homogeneous user-course interaction graph, retaining only the social regularization	0.745	0.602
HIN-SR	Complete model	0.892	0.756

Through systematic ablation experiments on the HIN-SR model, the contributions of each core component and their interrelationships are clearly revealed. The experimental results clearly point out that the heterogeneous information network structure is the cornerstone of the performance of the whole model, and the removal of this structure (w/o HIN) leads to a sharp decline of 16.5% in HR @ 10 index, which fully demonstrates that it is indispensable to use meta-path to model complex semantic relationships among learners, courses, knowledge concepts and other entities. The rich structural information it provides is far from being replaced by social relations. On this basis, the social regularization component plays a key role, and its removal (w/o SR) causes a significant decrease of 6.8% in HR @ 10, confirming that the deep integration of social relations into representation learning is essential to alleviate data sparsity and improve recommendation accuracy. Furthermore, the influence weighting mechanism brings additional refinement gains. Although the performance degradation caused by its removal (w/o INFL) is relatively slight, this quantitative difference confirms that it is effective to distinguish user influence, and the behavior patterns of high-influence learners (such as opinion leaders) do have higher reference value. To sum up, the performance of the model depends on the organic synergy of the semantic basis provided by heterogeneous networks, the trust constraints injected by social relations, and the fine adjustment achieved by influence weighting. To quantify the contribution of each core component in the HIN-SR model, we visualize the results as a performance decay histogram, as shown in Figure 6.

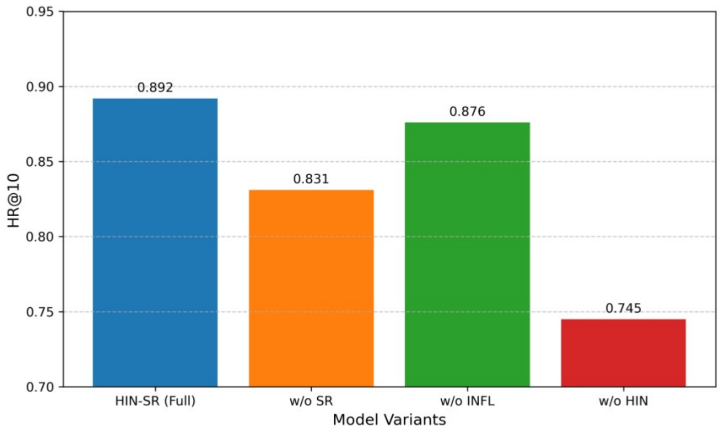

Figure 6 Visualizes the Performance Degradation Histogram

5.4 Cold start scenario analysis

The cold-start problem, i.e., how to provide effective recommendations for new users with minimal or even zero historical interactions, is a key challenge that any practical recommender system must overcome, especially in educational scenarios. Traditional collaborative filtering methods almost fail in such scenarios, while social recommendation is considered as a potential solution, because it can infer the interests of new users with the help of their limited social connections. This section aims to empirically assess the robustness and unique advantages of the HIN-SR model in meeting this challenge. We strictly define users with less than 5 interaction records in the dataset as cold-start users, and contrast the performance of HIN-SR with the main baseline model on this subset of users. Figure 7 shows the HR @ 10 performance of each model in the cold start user population on the XuetangX data set.

HIN-SR shows the strongest robustness in the cold start scenario. Its HR @ 10 reaches 0.723, which is significantly higher than EGRec (0.658) and TrustSVD (0.601). This is because HIN-SR can find its neighbors in the social network for cold-start users through meta-paths, and even if its own interaction is very small, it can also get a reasonable embedding representation through the behavior and characteristics of the neighbors. At the same time, the social regularization term encourages the embedding of cold-start users to move closer to the embedding of their trusted friends, which further provides prior information. This proves that HIN-SR can effectively use social networks and heterogeneous relationships to alleviate the cold-start problem. This experiment not only aims to verify the superiority of HIN-SR over other methods, but also focuses on revealing the underlying mechanism, that is, how the model constructs a still informative embedded representation for learners with sparse data by effectively utilizing the high-order semantic associations contained in heterogeneous information networks, as well as the trust and influence propagation enhanced by dual social regularization. O as to realize the recommendation effect superior to the traditional method. In the following, the experimental results will be analyzed in detail, and its technical connotation will be discussed in depth.

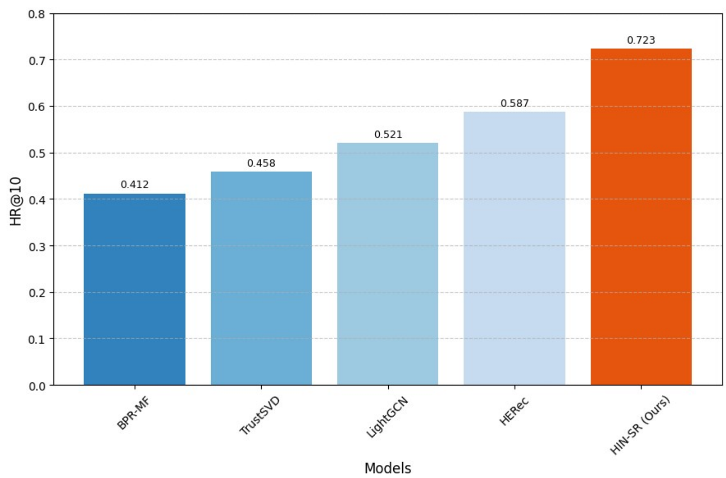

Figure 7 Cold Start User Performance Comparison (HR@10)

5.5 Hyperparameter sensitivity analysis

After verifying the effectiveness of the core components of the HIN-SR model, sensitivity analysis of its key hyperparameters is a necessary step to evaluate the robustness of the model and guide the optimization of practical applications. The performance of the HIN-SR model, in particular its ability to balance the fusion of heterogeneous structures with social signals, is subject to social regularization weights α and β. A significant impact. The purpose of this section is to systematically explore the patterns and rules of the impact of different combinations of these two key hyperparameters on the final recommendation performance of the model. We will observe different values on the validation set by grid search. α, β), and draw the sensitivity thermal map. The results of the thermodynamic map presented in Figure 8 will provide an intuitive basis for the selection of hyperparameters and reveal the deep law of the interaction between social signals and structural signals within the model.

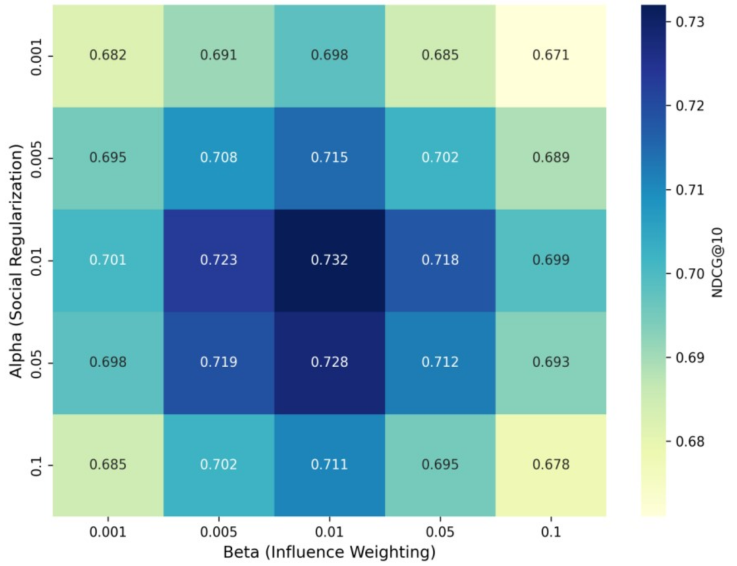

Figure 8 Social Regularization Hyperparameter Sensitivity Analysis

We analyze the social regularization weight λ_{trust} and $\lambda_{inf\,1}$ impact on model performance. Experiments have shown that when λ_{trust} is around 0.01, $\lambda_{inf\,1}$ is in the vicinity of 0.001, the model achieves optimal performance. Too large regularization weights can over-constrain the model, resulting in under-fitting. If they are too small, they can not make full use of social information.

6. Summary and Outlook

This paper proposes and validates a novel social recommendation model named HIN-SR, designed to address core challenges such as data sparsity and underutilised social relationships in large-scale online learning environments. By constructing a unified heterogeneous information network that integrates a heterogeneous graph attention network with a dual social regularisation mechanism, the model achieves a synergistic modelling of complex structural semantics and differentiated social influences within the learning ecosystem. Theoretically, the study identifies key elements of social recommendation in educational settings and proposes a comprehensive analytical framework; technically, the proposed dual social regularisation mechanism enhances the modelling of social relationships. Experiments on the MOOCCube and XuetangX datasets demonstrate that HIN-SR outperforms state-of-the-art baseline models in both course and peer recommendation tasks, whilst exhibiting robust performance in cold-start scenarios. In practice, this model provides MOOC platform designers with a technical framework for integrating multi-source heterogeneous data and building intelligent recommendation services. Its ability to mitigate the cold-start problem aids user retention, whilst its integrated design is expected to enhance learner engagement and completion rates by improving recommendation accuracy and enhancing social presence. Despite these positive results, this study has limitations: future work could involve dynamic modelling of user interest drift and the evolution of social relationships; improving the model's interpretability; exploring training paradigms based on federated learning or differential privacy to protect user privacy; and further validating the model's generalisation capabilities in more diverse scenarios such as corporate training and blended learning.

Conflict of Interest

The authors declare that they have no conflicts of interest in this work.

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