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PAPER

Driving the Integration of Mobile Learning and Blended Learning Models in Higher Education

Wen Zhao(✉)

Network Information Center,
Zibo Vocational Institute,
Zibo, China

zhaowen@zbvc.edu.cn

ABSTRACT

With the rapid advancement of information technology, particularly the widespread adoption of mobile internet, the integration of mobile learning and blended learning models in higher education has emerged as a significant innovation in educational practice. Vocational education, as an educational model that emphasizes practical skills and applied abilities, faces challenges in effectively combining these two approaches. The pervasive use of mobile devices enables learners to engage in learning at any time and location, yet it raises critical issues related to the construction of efficient interactive learning networks and the enhancement of learning outcomes. Consequently, study on "mobile device-to-mobile device" offline blended learning interaction networks has gained prominence. These networks not only prioritize interaction and collaboration among learners but also aim to provide personalized and precise learning support in multidimensional and dynamic learning environments. While existing studies have yielded insights into the integration of mobile learning and blended learning, as well as the design of learning interaction networks, they often lack in-depth exploration of complex learning interaction models and dynamic data relationships. Additionally, traditional learning network models frequently suffer from limited adaptability and insufficient accuracy in practical applications. In particular, as for the construction and optimization of "mobile device-to-mobile device" offline learning interaction networks, robust theoretical frameworks and practical solutions are lacking. Therefore, this study focuses on the definition and link prediction challenges of such networks. Through scientific model design and algorithmic optimization, the study seeks to enhance interaction efficiency and personalized support within learning networks, thereby advancing innovation and development in educational models.

KEYWORDS

mobile learning, blended learning, offline learning interaction networks, link prediction, personalized learning, educational technology

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1 INTRODUCTION

The rapid advancement of information technology, particularly the proliferation of mobile internet, has catalyzed profound transformations in the field of education [1–4]. Within vocational education, the integration of information technology has not only driven innovation in traditional teaching models but has also enhanced the diversity and flexibility of learning methods [5, 6]. Mobile learning and blended learning, as two predominant contemporary teaching approaches, have been extensively adopted in higher education, particularly in domains such as skill training, online education, and autonomous learning. These technological advancements have enabled learners to transcend the temporal and spatial constraints of conventional classrooms, allowing for learning and interaction at any time and place [7–12]. In particular, the development of "mobile device-to-mobile device" offline blended learning interaction networks has fostered a trend toward more open, flexible, and personalized educational models. However, effectively combining mobile learning and blended learning to address the growing learning demands in higher education remains a pressing research challenge.

The exploration of this topic holds significant theoretical and practical value. On one hand, the integration of mobile learning and blended learning models not only facilitates more flexible learning pathways but also promotes the optimized allocation of educational resources and the realization of personalized teaching. On the other hand, vocational education, which aims to cultivate high-quality application-oriented talent, is characterized by unique individualized learning processes and needs. Designing efficient learning interaction networks and improving learning outcomes through technological means have become critical directions of research in the educational domain [13–16]. Therefore, this study aims to examine the construction pathways and optimization strategies of "mobile device-to-mobile device" offline blended learning interaction networks, thereby providing new theoretical support and practical guidance for the innovation of educational models.

Despite the progress made in integrating mobile learning with blended learning and designing interaction networks, several limitations persist [17–19]. First, many studies have predominantly focused on theoretical exploration, lacking an in-depth analysis of practical issues encountered in specific application scenarios. Second, existing learning interaction network models tend to oversimplify the complexities of relationships and dynamic interactions among learners. These models often fail to incorporate effective mechanisms for adaptability and personalized recommendations. Furthermore, in-depth investigations into "mobile device-to-mobile device" offline blended learning interaction networks, along with optimization strategies, remain relatively scarce. In particular, enhancing the precision and real-time performance of learning networks through technological means warrants further research.

The main research content of this study includes two aspects. First, the relevant definitions of "mobile device-to-mobile device" offline blended learning interaction networks were proposed and discussed, with a focus on analyzing their structures, functionalities, and distinctions from traditional learning models. Second, the link prediction problem in offline blended learning interaction networks was investigated to explore how algorithms and models can improve the efficiency and accuracy of learner interaction and content dissemination within these networks.

By addressing these two aspects in-depth, this study aims to provide a more scientific and flexible pathway for mobile learning and blended learning models in higher education, promote the development of personalized education for learners, and offer both theoretical support and practical guidance for the further application of educational technology.

2 DEFINITIONS RELATED TO "MOBILE DEVICE-TO-MOBILE DEVICE" OFFLINE BLENDED LEARNING INTERACTION NETWORKS

In "mobile device-to-mobile device" offline blended learning interaction networks, the integration of mobile learning and blended learning models results in frequent and complex interactions between learners and teaching content, forming a large, dynamically evolving network. Within this network, the relationships among learners continuously change, and both the content and modes of learning adapt to various learning scenarios and requirements. As a result, traditional static content representation models have become insufficient for addressing the demands of such a complex environment. Tensors, as multidimensional arrays, offer a flexible and efficient approach to modeling dynamic and heterogeneous learning networks by simultaneously considering multiple factors such as learners, teaching content, time, and space. In this study, a tensor-based model was proposed to accurately represent the multifaceted relationships between learners and teaching content while handling large-scale and high-dimensional data, thereby providing more intelligent support for learning processes.

2.1 Triplet representation of tensor-based learning interaction networks

In "mobile device-to-mobile device" offline blended learning interaction networks, learners not only engage in self-directed learning via mobile devices but also collaborate and communicate with other learners. Consequently, the dissemination of learning content and the change of learning behaviors constitute a multidimensional and dynamic process. The interactions and information exchanges among learners are inherently complex and multidimensional, rendering traditional matrix-based representation methods inadequate for effectively capturing these intricate relationships. To better represent learner interactions, the dissemination of learning content, and their dynamic changes, triplet tensors were adopted as a representation tool for the precise depiction of interactions between learners and the pathways of content dissemination. Specifically, each interaction relationship within the learning interaction networks can be represented as a multidimensional data unit via triplet tensors, where each dimension corresponds to a distinct vector space, reflecting interaction characteristics across different dimensions. For instance, the dimensions can represent learners, learning content, and attributes such as interaction time or space, while the tensor elements denote specific relationships among these dimensions, such as a learner engaging with specific content at a particular time. Specifically, for a third-order tensor A, the element A_{gjs} can be used to represent the j-th interaction relationship established between the s-th learner and the g-th learner. Figure 1 illustrates an example of triplet representation for "mobile device-to-mobile device" offline blended learning interaction networks.

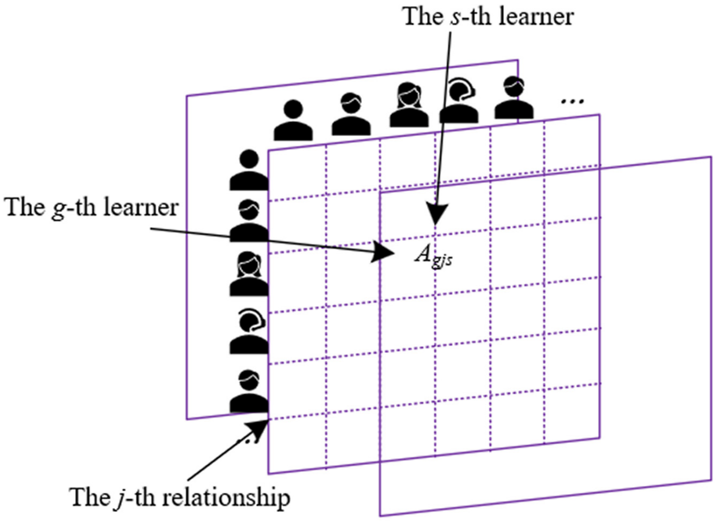


Fig. 1. Example of triplet representation in "mobile device-to-mobile device" offline blended learning interaction networks

2.2 Relationship representation in learning interaction networks based on slices

To effectively represent "mobile device-to-mobile device" offline blended learning interaction networks, the concept of tensor slices was introduced as a two-dimensional component of the network relationships. Specifically, tensor slices are defined by fixing all but two indices within the tensor, allowing specific relationships to be represented. This approach enables researchers to extract particular interaction patterns from the tensor. For instance, in a third-order tensor A, a slice A_u represents all elements of the first dimension while fixing the second and third dimensions. Similarly, a slice A_k fixes the first and third dimensions while representing all elements of the second dimension, and a slice A_j fixes the first and second dimensions while representing all elements of the third dimension. Through this method, tensor slices can efficiently extract the interaction relationships among learners, learning content, time, and other multidimensional information into a plane, thereby reducing the complexity of relationship representation.

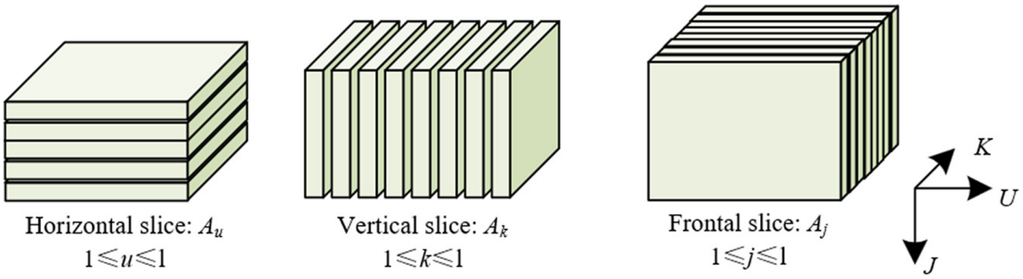


Fig. 2. Relationship representation of "mobile device-to-mobile device" offline blended learning interaction networks based on slices

Figure 2 illustrates a schematic representation of "mobile device-to-mobile device" offline blended learning interaction networks based on slices. In this representation, if A_j is used to denote the interaction relationship between a specific learner and another learner, the slice A_j can explicitly indicate whether an interaction exists between the two learners in a particular time frame or learning scenario. When a relationship link is present, the corresponding element a_{ukj} in A_j is assigned a value of 1, signifying that the interaction between the two learners at that specific time is valid.

2.3 Graph of "mobile device-to-mobile device" offline blended learning interaction networks

The traditional learning interaction network graph is typically represented using an undirected graph $H = \{N, R\}$, where N denotes the set of learners and R represents the set of relationships among learners. In such models, the edge R represents the interaction relationship between learners, such as file type, sharing time, or geographical information. These edges are generally undirected, indicating that the initiator and recipient of interactions cannot be distinguished. However, in large-scale learning interaction networks, particularly in "mobile device-to-mobile device" offline blended learning environments, learners not only engage in autonomous learning via devices but also collaborate in physical spaces. Furthermore, the dissemination of learning content often exhibits directionality. Consequently, traditional undirected graphs are insufficient to effectively deal with complex interactive directions among learners, content dissemination paths, and personalized learning needs. In order to better adapt to this demand, a learning interaction network graph model based on directed graphs was proposed in this study. That is, the directed graph $H = (N_G, R, N_S)$ is used to represent the "mobile device-to-mobile device" offline blended learning interaction networks, where N_G represents the source learner (i.e., the initiator of information), N_S represents the target learner (i.e., the recipient of information), and R denotes the set of directed relationships of learning content dissemination, reflecting the direction of interaction and information flow among different learners.

In this directed graph-based learning interaction network graph, learner nodes not only have identity information but also may contain personal tags such as geographic location and learning interests. These attributes make each learner's behavior more diverse, reflecting their unique needs and characteristics in the learning process. For instance, geographic information can facilitate the analysis of learners' behaviors within specific spatiotemporal contexts and their interaction patterns with others. Such analyses are particularly valuable for tasks such as group segmentation and community detection. Additionally, the edge relationship in the learning interaction network graph can capture the directionality of dissemination, i.e., how information spreads from one learner to another in a certain learning activity. This directed relationship not only accurately reflects the dissemination path of learning content but also reveals the differences between the source and receiver of the content during the learning process.

2.4 Representation learning for "mobile device-to-mobile device" offline blended learning interaction networks

Given a learner relationship graph consisting of v learners and l content dissemination relationships, the graph comprises the set $S^+ = \{(g, s, j)\}$ of multiple "learner-content dissemination relationship-learner" factual triplets. Each triplet represents an interaction between a source learner g and a target learner s through a content dissemination relationship *j* at a specific time. Representation learning was employed to map each learner and each dissemination relationship into a low-dimensional vector space. These vectors effectively reflect the interactions among learners, the dynamic characteristics of content dissemination, and the behavioral patterns of individual learners. For instance, if the interaction between learner *g* and learner *s* occurs through relationship *j*, their vector representations can be used as a learning objective, which enables the vectors of similar learners and dissemination relationships to be positioned closer, thereby facilitating subsequent tasks such as predicting implicit relationships within the learning networks, analyzing learner behaviors, and optimizing content dissemination patterns.

This representation learning approach based on low-dimensional vectors is suitable for "mobile device-to-mobile device" offline blended learning interaction networks and has significant advantages, especially when dealing with large-scale and dynamically changing learning interaction networks. In such networks, learners not only are static nodes but also have rich attribute labels, such as geographical location, interests, preferences, and learning history. These labels can be integrated into the learning process as feature information to help construct more refined relationship vectors. By incorporating this multidimensional information, representation learning can not only reveal direct learning interactions between learners but also explore deeper patterns of group behavior and the pathways of learning content dissemination and other information. For example, utilizing geographical location information, online learning activities, and offline learning interaction data of learners, a vector representation with high explanatory power can be generated for each learner in the low-dimensional space.

3 LINK PREDICTION IN "MOBILE DEVICE-TO-MOBILE DEVICE" OFFLINE BLENDED LEARNING INTERACTION NETWORKS

Traditional tensor decomposition methods, such as the relational scalable tensor factorization (RESCAL) model, can be used to model relationships between learners through low-dimensional vectors. However, these methods face limitations when applied to large-scale and complex networks. The conventional RESCAL model typically represents edges in a network as binary or continuous values, failing to effectively capture the rich and diverse features embedded in the edges. Particularly in real-world "mobile device-to-mobile device" offline blended learning interaction scenarios, content interactions between learners often exhibit high frequency, dynamic characteristics, and diverse behaviors. For instance, learner interactions during the learning process are not limited to simple exchanges but encompass various types of content dissemination, such as sharing learning resources, discussions, and feedback. These behaviors are strongly influenced by temporal and spatial factors. Traditional tensor decomposition methods are insufficient to accurately represent such multidimensional and dynamically evolving learning interactions, making it challenging to fully explore these complex relationships and predict future interaction behaviors. To address these limitations, a probabilistic tensor representation learning model was introduced in this study, which can more accurately capture the stochastic and complex nature of interactions between learners.

In "mobile device-to-mobile device" offline blended learning interaction networks, learners exhibit highly personalized behaviors and interaction preferences. Traditional learning interaction network graph models often describe learners and content dissemination relationships using simple nodes and edges, which fail to adequately capture the complex behavioral patterns and emotional connections between learners. For example, learners with similar interests may share the same types of learning resources, such as mobile applications, articles, or videos. The dissemination of such content is influenced by specific behavioral preferences, including geographic location, sharing time, and interaction frequency. To more accurately describe the learning interactions within these networks, the learning interaction network graph was redefined to better reflect the diversity and complexity of learner behaviors. In this new definition, the learning interaction networks not only include learners and edges but also distinguish between source learners and target learners, thereby refining the directionality of content dissemination. This distinction enables the identification of the origins and recipients of information flow. In the newly defined graph model, established social relationships or shared learning resources among learners can be distinguished, while potential learning behaviors between learners can also be predicted to expand the network's structure. The primary advantage of this model lies in its ability to predict future interactions by leveraging multidimensional information such as file type, sharing time, and geographic data. This allows for the better identification of potential learning content dissemination pathways in large-scale learning networks and recommends personalized learning resources to learners. Specifically, in the graph embedding-based offline blended learning interaction networks, a directed graph $H = \{N_G, R, N_S\}$ is considered, where $N = N_G \cup N_S$ represents the set of learner vertices, with N_G denoting source learners and N_G denoting target learners. The set $R \subseteq N_G \cup N_S$ consists of multiple interaction relationships on edges. Additionally, the edge R can be represented as N_M or N_O, leading to the condition $R = R_{MI} + R_O$.

In "mobile device-to-mobile device" offline blended learning interaction networks, the interaction relationships among learners are often complex and dynamic, which cannot be described simply by their existence or absence. Traditional binary rating mechanisms are insufficient for capturing fine-grained details of interaction behaviors within the networks, especially when interactions among learners involve not only occasional occurrences but also frequent content sharing, commenting, feedback, and other diverse behavior patterns. To model these complex and temporally variable interaction relationships more accurately, a probabilistic relationship rating mechanism was adopted in this study. Specifically, probabilistic ratings introduce uncertainty into the construction of triplet tensors and use probability values to reflect the strength and likelihood of interaction relationships among learners. In the implementation of probabilistic relationship ratings, triplet tensors were constructed by treating each interaction relationship in the learning interaction networks as a triplet with probability. For this purpose, the residual network (ResNet) model was utilized, which decomposes a third-order tensor into a feature matrix r and a core tensor Q. This decomposition effectively captures the multidimensional relationships among learners and the complexity of content dissemination. In this model, f represents the number of feature factors, which controls the model's complexity and expressive capability. Specifically, when an interaction relationship exists among learners, the ResNet model evaluates the validity of the corresponding triplet by calculating a probability value O_{gsj}, thereby further predicting the possibility of unobserved future interaction relationships. Let r_g and r_s represent a $v \times f$ matrix, where v denotes the number of learners in observation data and f represents the embedding dimension for each learner. The interaction relationship of type j between learners is represented by an anti-symmetric matrix Q_j of size $f \times f$. The decomposition of the third-order tensor, or the scoring function, can be expressed as follows:

$$\psi(g, s, j) = A_j = r_g^S Q_j r_s \tag{1}$$

Assuming the Sigmoid activation function is denoted as $\delta(a) = 1/1 + e^{-a}$, the log-odd predicted probability ($rh,O_{vsj} = O(B_{gsj} = 1)$) for relationship $e(g,s)$ being correct is expressed by O_{gsj}, where $O_{gsj} \in \{0,1\}, \forall u,k,j$. The formula for predicting the probability of the relationship $e(g,s)$ is given as:

$$O_{gsj} = \delta(\Psi(g, s, j)) \tag{2}$$

where, $a_{ukj} = O_{gsj}$. The relationship probability can be reformulated as:

$$O_{gsj} = a_{ukj} = \delta(\Psi(g, s, j)) = O(B_{gsj} = 1) \tag{3}$$

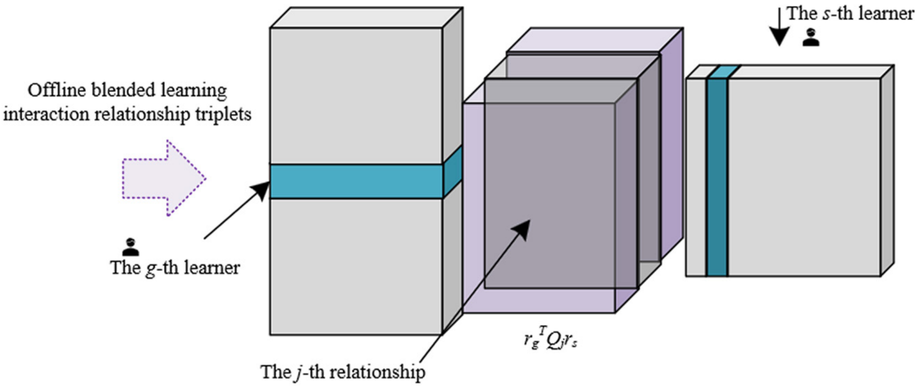


Fig. 3. Decomposition process of the third-order tensor for triplets in "mobile device-to-mobile device" offline blended learning interaction network relationships

In "mobile device-to-mobile device" offline blended learning interaction networks, learners form complex learner-content dissemination relationship-learner triplets through content sharing and interaction. The modeling of these triplets serves as the core representation of interaction relationships. Given that these interactions involve multidimensional information and exhibit temporal and dynamic variability, the model must efficiently handle large-scale data while capturing the complexity and evolution of these relationship patterns. To address these requirements, a combination of the mini-batch stochastic gradient descent (SGD) and the Adaptive Gradient Algorithm (AdaGrad) was employed for training the link prediction model in these networks. Furthermore, the incorporation of an L2-regularized negative log-likelihood loss function helps the model to identify more compact and efficient relationship patterns by minimizing errors. This training strategy not only enhances the model's ability to recognize complex relationship patterns but also improves its adaptability to new learners, behaviors, and content in practical applications. The modeling process for the constructed model in the third-order tensor space is illustrated in Figure 3. Let the regularization coefficient be denoted as η. The proposed model minimizes the objective function for the factor matrix r_g, r_s, and Q_j in the probabilistic scoring tensor, expressed as:

$$\underset{r_g, Q_j, r_s}{MIN} \sum_{e(g,s)\in\Pi} d\left(r_g, Q_j, r_s\right) + h\left(r_g, Q_j, r_s\right) \tag{4}$$

where,

$$d(r_g, Q_j, r_s) = \log(1 + \exp(-B_{gsj}\Psi(g, s, j))) \tag{5}$$

$$h\left(r_g, Q_j, r_s\right) = \eta\left(\left\|r_g\right\|_2^2 + \left\|Q_j\right\|_D^2 + \left\|r_s\right\|_2^2\right) \tag{6}$$

Let the training set used during the model training phase be represented by Π. Equation (4) can then be transformed into the following form:

$$\varepsilon(\Pi) = \sum\nolimits_{e(g,\, s) \in \Pi} d(r_g, Q_j, r_s) + h(r_g, Q_j, r_s) \tag{7}$$

The optimization of $d(r_g, Q_j, r_s)$ was addressed using the mini-batch SGD method. The gradient expression for the parameter-optimized scoring function is given as:

$$\nabla_{r_g}\psi(g, s, j) = Q_j r_s, \nabla_{Q_g}\psi(g, s, j) = r_g r_s^S, \nabla_{r_s}\psi(g, s, j) = Q_j^S r_g \tag{8}$$

Finally, the gradient representation for the learner relationship triplet $e(g,s)$ can be reformulated. The following expression provides the optimization problem for the embedding representation by considering $\varepsilon(\Pi)$:

$$\begin{aligned}
\nabla_{r_g}\varepsilon(e(g, s)) &= -B_{gsj}\psi(g, s, j)\delta\left(Q_j r_s\right) + 2\eta r_g \\
\nabla_{Q_g}\varepsilon(e(g, s)) &= -B_{gsj}\psi(g, s, j)\delta\left(r_g r_s^S\right) + 2\eta Q_j \\
\nabla_{r_s}\varepsilon(e(g, s)) &= -B_{gsj}\psi(g, s, j)\delta\left(Q_j^S e_g\right) + 2\eta r_s
\end{aligned} \tag{9}$$

To enhance the model's discrimination ability and learning efficiency, a "positive triplet and negative triplet sample" strategy was employed in conjunction with the mini-batch SGD algorithm during training. Specifically, the training process begins with the generation of initial learners and the random embedding of content relationships. These embeddings represent the potential interactions between learners and content, and the interactions among learners are expressed in the form of positive triplets. During the training phase, the model needs to optimize these embedding vectors by minimizing the loss function. In addition to positive triplet samples, negative triplet samples are generated to improve training effectiveness and model accuracy. Negative samples are created based on the local closed-world assumption. Either the head entity or the tail entity of a positive triplet is randomly perturbed to generate several negative samples. The generation simulates non-existent interactions, which enables the model to distinguish between authentic and non-authentic interactions during training, further enhancing its discriminatory capability.

Compared to traditional full-batch gradient descent methods, mini-batch SGD is more efficient in handling large-scale datasets. Particularly in "mobile device-to-mobile device" offline blended learning interaction networks, which are characterized by the vast number of learners, diverse content types, and complex dynamic interactions, mini-batch training reduces memory overhead and accelerates the training process. Each mini-batch consists of a combination of several positive and negative samples. Gradients are computed and model parameters are updated during the training process, guiding the embedding vectors toward an optimal solution. Therefore, the mini-batch SGD algorithm was used to optimize model parameters in the training process. In addition, the AdaGrad optimizer was applied to adaptively adjust the learning rate of each parameter, which helps the model to dynamically adjust the step size during the training process, preventing gradient explosion or vanishing caused by excessive updates.

4 EXPERIMENTAL RESULTS AND ANALYSIS

When analyzing the link prediction model for “mobile device-to-mobile device” offline blended learning interaction networks, significant effects of varying regularization parameters on model performance were observed. As shown in Figure 4, with an increase in the regularization parameter, the model’s performance metrics, including mean reciprocal rank (MRR) and *Hits*@1, *Hits*@3, and *Hits*@10, initially improved and subsequently stabilized. For instance, when the regularization parameter was set to 0.4, the MRR reached its peak value of 0.675, while *Hits*@1, *Hits*@3, and *Hits*@10 achieved relatively high levels of 0.685, 0.69, and 0.705, respectively. These findings indicate that, within a certain range, moderate regularization effectively enhances the model’s predictive capability, improving the efficiency of interactions and content dissemination among learners. The analysis underscores the critical importance of selecting appropriate regularization parameters for model performance. Insufficient regularization may lead to overfitting, while excessive regularization could suppress the model’s learning capacity. The experimental results suggest that optimal performance can be achieved when the regularization parameter is within the range of 0.4 to 0.6, which balances the complexity and generalization capability of the learning networks.

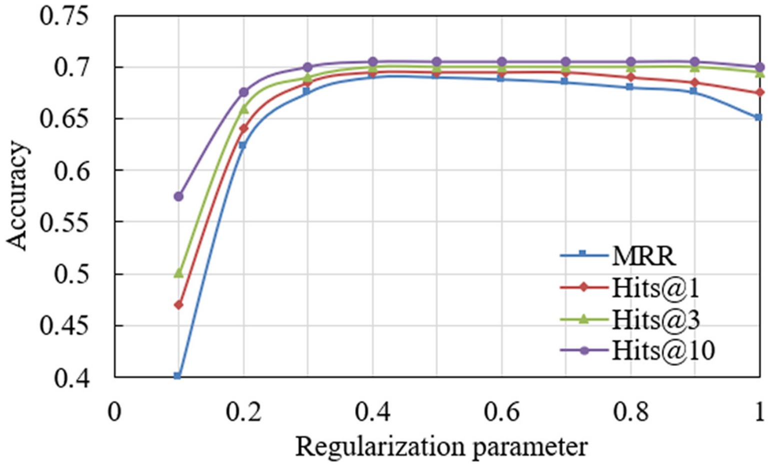


Fig. 4. Performance variation of the constructed interaction network link prediction model under different regularization parameters

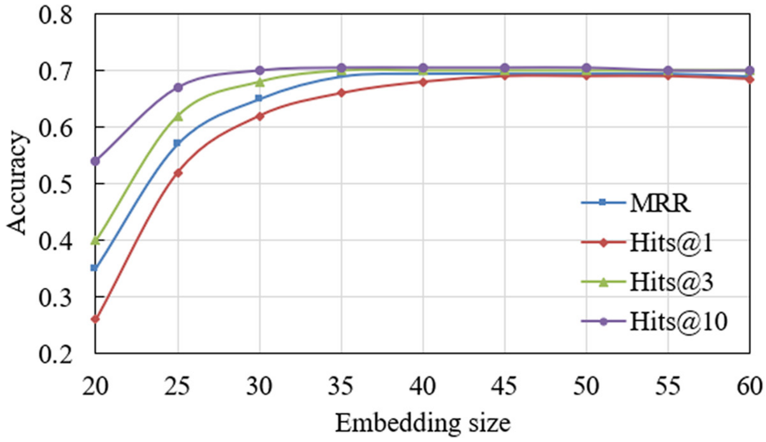
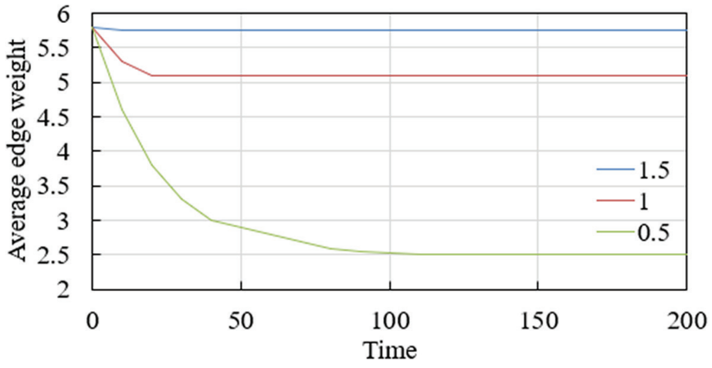


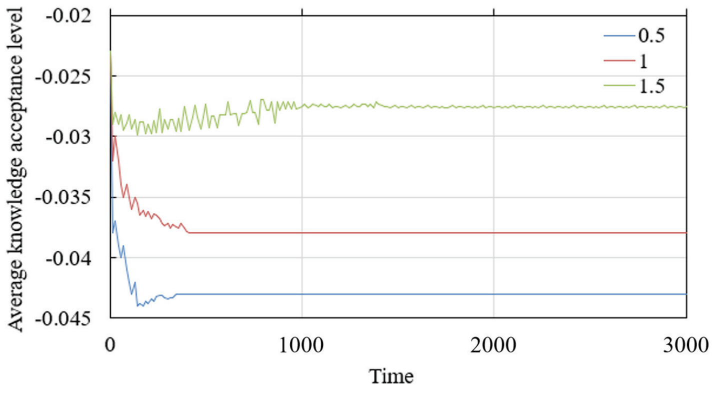
Fig. 5. Performance variation of the constructed interaction network link prediction model under different embedding dimensions

Based on the data presented in Figure 5, an overall upward trend in performance metrics, including MRR, *Hits*@1, *Hits*@3, and *Hits*@10, is observed as the embedding dimension increases. At an embedding dimension of 20, the performance metrics remain relatively low, with MRR at 0.35, *Hits*@1 at 0.26, *Hits*@3 at 0.4, and *Hits*@10 at 0.54. However, as the embedding dimension increases to 50, MRR improves significantly to 0.695, *Hits*@1 increases to 0.69, and *Hits*@3 and *Hits*@10 reach 0.7 and 0.705, respectively. This indicates that higher embedding dimensions contribute to better prediction accuracy and effect of the model. Further increases in the embedding dimension, such as to 55 and 60, do not result in substantial improvements, with MRR and other metrics stabilizing within the range of 0.695 to 0.69. This suggests that the increase in dimensions thereafter has stabilized the improvement in model performance.

The analysis highlights the positive impact of increasing embedding dimensions on model performance, particularly within the range of 20 to 50, where significant improvements are observed. At lower embedding dimensions, such as 20, the model's expressive capacity is limited, preventing it from effectively capturing the interactions among learners and content dissemination information, thereby reducing prediction accuracy. Once the dimension reaches 50, the model sufficiently captures the complexities of learner interaction relationships, and the effect of further increasing dimensions on improving performance gradually weakens. Therefore, for link prediction in "mobile device-to-mobile device" offline blended learning interaction networks, selecting an appropriate embedding dimension is a suitable strategy, which sufficiently improves the effect of learner interactions in the learning networks while avoiding excessive computation and memory usage. These findings are crucial for improving the efficiency and accuracy of mobile learning and blended learning models in higher education.



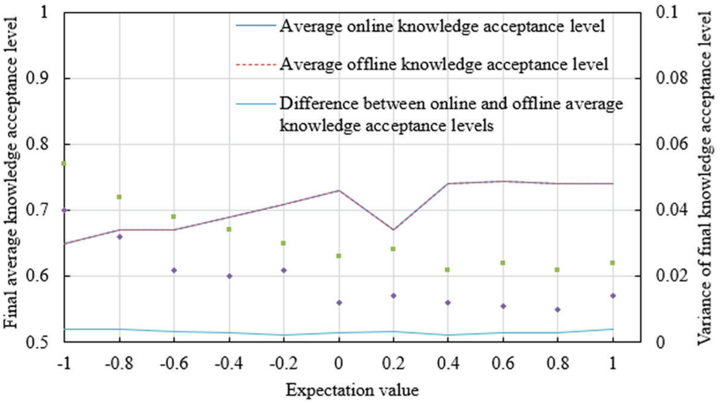
a) Average Network Edge Weight



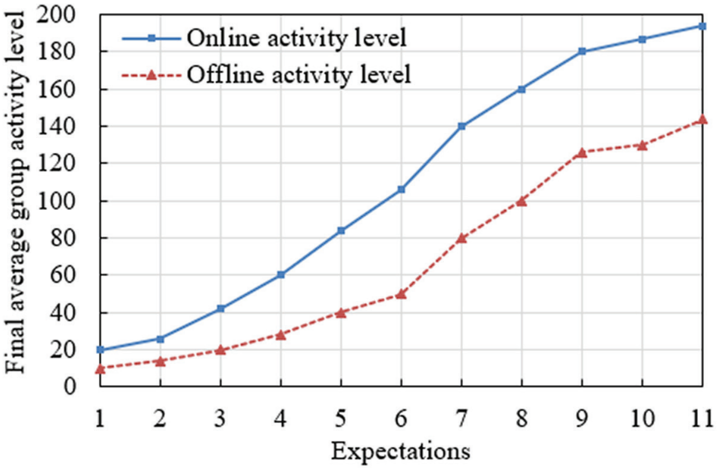
b) Average Knowledge Acceptance Level

Fig. 6. Variations in average network edge weight and average knowledge acceptance level under different interaction acceptance levels

The data presented in Figure 6 encompass two aspects: the relationship between average network edge weight and interaction acceptance level, and the relationship between average knowledge acceptance level and interaction acceptance level, with data changing over time. For each time point, the values corresponding to interaction acceptance levels exhibit distinct variation patterns. From the data shown in Figure 6a, a clear relationship is observed between average network edge weight and interaction acceptance level. At higher interaction acceptance levels, the average network edge weight remains large, stabilizing at relatively high levels over subsequent time points. This indicates that under conditions of high interaction acceptance levels, the network edge weights do not exhibit significant fluctuations. However, when the interaction acceptance level decreases to 0.5, a marked reduction in average network edge weight is observed, declining from approximately 5.8 to around 2.5. This trend demonstrates that as the interaction acceptance level diminishes, the closeness of interactions among learners and the efficiency of content dissemination within the networks gradually decline. The average knowledge acceptance level reveals a downward trend as the interaction acceptance level decreases. For instance, at an interaction acceptance level of 0.5, the average knowledge acceptance level begins at –0.023 and gradually decreases over time, reaching approximately –0.044. This suggests that as interaction relationships weaken, the acceptance level of knowledge within the networks is reduced. A possible explanation is that the reduced frequency of interactions diminishes the effectiveness of knowledge dissemination.



a) Average Knowledge Acceptance Level



b) Learner Activity Level

Fig. 7. Variations in average network knowledge acceptance level and learner activity level along with knowledge acceptance expectations

Figure 7 illustrates distinct patterns in network knowledge acceptance level and learner activity level as the number of head entities varies. For both online and offline knowledge acceptance levels, similar trends of their average values are observed. As the number of head entities increases from –1 to 1, the knowledge acceptance level shows a gradual upward trend. In particular, within the range of 0 to 1, online and offline knowledge acceptance levels converge and stabilize, remaining consistently between 0.67 and 0.74. It is noteworthy that the variance of online knowledge acceptance levels fluctuates significantly, ranging from 0.054 to 0.022, indicating differences in the distribution of online knowledge acceptance levels across varying numbers of head entities. In contrast, the variance of offline knowledge acceptance levels remains relatively small, fluctuating between 0.04 and 0.01, demonstrating higher stability.

Additionally, the difference between online and offline knowledge acceptance levels remains approximately constant, between 0.51 and 0.52, indicating minimal disparity between the two modes and consistent behavior with changes in head entity count. Regarding learner activity level, a pronounced increase in online activity level is observed as the number of head entities rises, growing from 20 to 194. This trend highlights the enhanced activity level of learners in online environments with the increased participation. Conversely, the offline activity level exhibits a more gradual increase, rising from 10 to 144, showing a steadier growth trajectory compared to the online activity level. This indicates that although the activity level of offline learning is lower than online learning, as the number of head entities increases, the activity level of offline learners gradually increases. This suggests that in the “mobile device-to-mobile device” hybrid learning mode, online learning can better stimulate learners’ activity levels, while offline learning still has good stability.

5 CONCLUSION

This study focused on “mobile device-to-mobile device” offline blended learning interaction networks, mainly studying two aspects. First, a definition of the interaction networks was proposed, accompanied by an analysis of their structure, functionality, and distinctions from traditional learning models. The networks’ ability to flexibly integrate online and offline resources was emphasized, demonstrating its potential to enhance the efficiency of learner interaction and knowledge transmission. Second, the problem of link prediction within the networks was investigated, employing algorithms and models to improve the accuracy and efficiency of learner interaction and content dissemination. The study findings indicate that as the number of head entities increases, both online and offline knowledge acceptance levels exhibit a gradual rise, eventually stabilizing. Particularly in networks with a larger number of head entities, learners demonstrated similar levels of knowledge acceptance with minimal fluctuations. The online learning’s activity level increased significantly, highlighting its strong advantage in fostering learner interaction and participation, while offline learning exhibited a steadier growth in its activity level, reflecting its stability. The application of the link prediction model further improved interaction efficiency among learners and optimized the transmission of knowledge.

This study demonstrates that “mobile device-to-mobile device” offline blended learning interaction networks can significantly enhance both knowledge acceptance level and activity level of learners. Online learning excels in interaction and efficiency, whereas offline learning provides superior stability. The use of the link prediction model enhances the interaction efficiency of learners. However, certain limitations remain. The dataset used in this study was relatively small, and the practical application of the model may be constrained by technological and data quality limitations. Future research could expand the sample size and explore the effects across different disciplines and cultural contexts in depth. Additionally, emotional analysis and psychological models could be integrated to investigate learners' emotional changes and psychological needs. With technological advancements, the accuracy of the link prediction algorithm can be further improved, and the application of artificial intelligence and big data in the learning networks could be explored to create more personalized and efficient learning experiences.

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7 AUTHOR

Wen Zhao, who earned her Master's degree from Shandong University, is currently employed at Zibo Vocational Institute. Her primary research area involves the application of information technology and methodologies in vocational education (E-mail: zhaowen@zbvc.edu.cn).