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Identification and Guidance of Intimate Relationships Among Students Based on Reinforcement Learning

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With regard to digital education management, the massive amounts of student behavioral data contain complex relationship information. Importantly, the intimate relationships of students have a significant impact on their mental health and the school's education and teaching environment. Traditional student relationship management methods and existing analysis technologies have limitations in processing complex data and guiding student relationships. This study proposes an intelligent fusion network (IFN) model, which consists of a feature extractor, an information integrator, and a decision generator. By harnessing the collaborative operation of multiple components, it analyzes student relationship data. Experiments on a public campus social relationship dataset show that the IFN model has an 80% relationship recognition accuracy and scores 85% for the effectiveness of guidance strategy, which is a significant improvement compared with the social network analysis model (recognition accuracy 40%, guidance strategy effectiveness 40%) and the support vector machine model (recognition accuracy 50%, guidance strategy effectiveness 50%). The research results confirm that the IFN model can effectively mine students' intimate relationship information and provide reasonable guidance strategies. This study provides scientific and accurate decision support for school education management, enriches the theoretical content of educational technology in relationship analysis and intervention, and also provides a reference for subsequent research on the integration of technology and educational concepts.

Keywords: student intimacy, intelligent fusion network, relationship identification, guidance strategy, educational technology

1. INTRODUCTION

In today's digital age, schools' educational management environment has undergone tremendous changes. The deep integration of computer technology has enabled students' various behaviors and relationships on campus to be recorded and analyzed in the form of data. An ordinary middle school generates thousands or even tens of thousands of student-related data every day through campus management systems, online learning platforms, etc. These massive amounts of data contain complex relationship information about students. For example, in a sample survey of 500 students, it was found that about 60% of the students said that their emotional state on campus would be significantly affected by their intimate relationships with other classmates, and nearly 30% of the students had experienced fluctuations in their academic performance due to intimate relationship problems, with an average fluctuation of about 20 points (out of 100).

Students' intimate relationships can affect their mental health. For instance, a psychological survey of 800 students showed that 40% of the students with conflicting or unstable intimate relationships experienced various degrees

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of anxiety, depression and other negative emotions, affecting the overall educational and teaching atmosphere of the school. In an evaluation of the educational quality of 10 schools, it was found that the overall teaching satisfaction of schools with better student intimate relationships could be improved by about 35%, and the incidence of student violations could be reduced by about 25%. However, traditional student relationship management relies mainly on teachers' experience and limited observation, a method that is ineffectual in the face of large and complex data and students' diverse behaviors. The development of computer technology, especially reinforcement learning technology, provides us with a new perspective and powerful tools to explore students' intimate relationships in depth, and provide effective guidance.

In the current related fields, many studies have used various technical means to analyze student relationships. Some studies use social network analysis methods to discover relationship patterns by constructing social network graphs for students, but this method focuses on static structural analysis and is unable to capture dynamic changes in student relationships and complex behavioral feedback. For example, in a case study of social network analysis applications in 20 schools, it was found that the accuracy of predicting the trend of student relationship changes was only about 40%. Other studies have used classification algorithms in machine learning to identify the categories of student relationships, but there are often limitations when processing high-dimensional and nonlinear data. Studies have shown that when the data exceeds 50 dimensions, the accuracy of traditional classification algorithms will drop by about 30%. As an emerging artificial intelligence technology, reinforcement learning is still in its infancy in terms of relationship identification and guidance. Although a small number of studies have attempted to apply this method to similar fields, such as in several small-scale student group experiments, simple behavioral guidance using reinforcement learning has achieved certain promising results, with a behavioral improvement rate of about 50%. However, most of these studies lack systematicity and comprehensiveness, and there is no mature theory or method that provides a comprehensive mechanism and effective application model of reinforcement learning in the specific and important field of student intimacy.

At present, the hot issues in this field are focused on ways to improve the accuracy of relationship recognition and design more effective guidance strategies. The controversial point is whether the data-driven method of reinforcement learning is really appropriate given the psychological development and educational laws , and whether it will ignore the uniqueness of individual students and the humanistic connotation of education due to excessive reliance on data. In this present research, an in-depth study is conducted on the identification and guidance of students' intimate relationships based on reinforcement learning. Specifically, the key issues to be addressed include how to build a reinforcement learning model suitable for the characteristics of students' intimate relationship data, how to improve the recognition accuracy and guidance effectiveness of the model in complex environments, etc.

The innovation of this study lies in the deep integration of reinforcement learning technology with the specific educational field of student intimacy. It proposes a comprehensive identification and guidance system, which is expected to increase the accuracy of relationship identification to more than 70% and increase the effectiveness of guidance strategies by about 40%. It is anticipated that the study will contribute a more scientific and accurate decision-making process that can support school education management, enrich the content of educational technology in relationship analysis and intervention in theory, help teachers more effectively identify and guide students' intimacy in practice, promote students' mental health and all-round development, and improve the overall education quality and atmosphere of the school. At the same time, it can also provide a useful reference and basis for subsequent related research in terms of technology application and integration of educational concepts.

2. LITERATURE REVIEW

2.1 Application of Related Technologies in Student Relationship Analysis

Social network analysis methods have been used to study student relationships to a certain extent, by constructing social network graphs for students in order to discover relationship patterns. However, research has shown that this approach has several shortcomings. In an in-depth study of social network analysis application cases in multiple schools, it was found that its prediction accuracy for the trend of student relationship changes is only about 40% [1]. This is mainly because it focuses on static structural analysis and therefore cannot fully capture the dynamic changes in student relationships and complex behavioral feedback, which greatly reduces its practical value. When complex and dynamic student relationship data are processed by this relatively static analysis method, a lot of important information is omitted or misinterpreted, leading to low predictive accuracy and other issues [2].

Several researchers have applied classification algorithms in machine learning in order to identify student relationships and determine their implications. However, when faced with high-dimensional and nonlinear student relationship data, this approach has obvious limitations. According to relevant research, when the data dimensions exceed 50, the accuracy of traditional classification algorithms will decrease significantly by about 30%. This problem of decreased accuracy caused by data characteristics makes it difficult for classification algorithms to achieve ideal results in student relationship analysis. Traditional classification algorithms cannot handle high-dimensional and nonlinear data characteristics effectively. Hence, this severely limits their ability to identify student relationship categories, and they are unable to classify and assess student relationships accurately [3,4].

As an emerging artificial intelligence technology, reinforcement learning has been applied in a small number of studies for the identification and guidance of student intimacy. In some small-scale student group experiments, the use of reinforcement learning for simple behavior guidance has achieved promising results [5,6], and the behavior improvement rate can reach about 50%. However, these studies lack systematicity and comprehensiveness as a whole. There is no mature theory and method for the in-depth mechanism and effective application model of reinforcement learning in the specific and important field of student intimacy. At present, this technology is still in its infancy in this regard, and its depth and breadth of application are far from enough. Many key issues such as adaptability in complex environments have not been properly resolved [7, 8], making it difficult to be effectively applied in large-scale student relationship analysis.

2.2 Hot and Controversial Issues in The Field

At present, the hot issues in this field are focussed mainly on two issues: how to improve the accuracy of relationship identification since neither social network analysis methods nor traditional machine learning classification algorithms have reached a satisfactory level in this regard, and reinforcement learning has potential but is not mature; and, how to design more effective guidance strategies. However, accurate identification is only the first step, and how to use effective strategies to positively guide students' intimate relationships is the ultimate goal. The solution to these two hot issues is crucial to the development of this field, and it is related to whether the identification and guidance of students' intimate relationships based on reinforcement learning can truly mature and be applied to actual education management.

In the field of education, the uniqueness of individual students and the humanistic connotation of education cannot be ignored. If the application of reinforcement learning cannot adequately handle these issues, then even if certain technical results are achieved, it will be difficult for this approach to be accepted and widely implemented in educational practice. This controversy indicates the potential conflict between technology and educational concepts, which needs to be explored in depth and balanced in subsequent research.

2.3 Comprehensive Evaluation of Existing Research and Future Prospects

In general, the current research in the field of student intimate relationship identification and guidance based on reinforcement learning is still in the development stage. Although there have been some attempts to apply social network analysis methods and machine learning classification algorithms, they all have their own shortcomings. Although reinforcement learning has potential, it has not yet matured. While previous studies provide some foundation and direction for subsequent in-depth exploration, they highlight the urgency of conducting more in-depth and comprehensive research in this field [9, 10]. Current research still has a lot of room for improvement in terms of the depth and breadth of technology application, and has not yet reached an ideal state regarding the integration of technology and educational concepts.

3. RESEARCH METHODS

3.1 Design and Operation of Feature Extractor

In the context of student intimacy analysis, data often contains complex topological information, which is crucial for identification and guidance. Therefore, this study uses a method based on graph neural networks (GNNs) to build a feature extractor in order to extract the most representative features from the raw data [11].

Assume the input data set is $\mathcal{D} = \{x_i\}_{i=1}^{N}$, where each x_i represents an individual student node, and the edge set $\mathcal{E}$. Then define the relationship connection between student nodes. Based on this, construct the adjacency matrix $A \in \mathbb{R}^{N\times N}$. Sum degree matrix $D \in \mathbb{R}^{N\times N}$. The feature extraction process can be described by the following mathematical formula, as shown in Formula (1) [12].

$$H^{(l+1)} = \sigma\left(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{1}$$

In the Formula (1), $H^{(l)}$, for the l, the feature representation of the layer, $W^{(l)}$ is a learnable parameter, $\sigma(\cdot)$ is a nonlinear activation function. As the number of network layers increases, the feature extractor can automatically identify and extract key features that are helpful for subsequent analysis, providing strong support for the work of subsequent model components [13, 14].

3.2 Operational Logic of Information Integrator

Student intimacy data has multimodal characteristics, and the data from different sources and in different forms are rich but complex. In order to effectively integrate these multimodal data, this study introduces an information integration strategy based on the attention mechanism in the information integrator.

Assume that the acquired features are represented as $F = \{f_i\}_{i=1}^{M}$, where each f_i Corresponding to a specific data source or feature type. To determine the importance of different features, the attention weight is calculated α_i. To dynamically adjust the fusion weight of features, to calculation formula is as shown in Formula 2 is used for the calculation.

$$\alpha_i = \frac{\exp(v^\top \tanh(W_a q;\, f_i))}{\sum_{j=1}^{M}\exp(v^\top \tanh(W_a q;\, f_j))} \tag{2}$$

In Formula (2), q is the query vector, W_a and v. This mechanism enables the information integrator to flexibly adjust the importance of each feature according to task requirements, ensuring that the integrated output contains the most relevant information and improving the model's ability to process complex data.

3.3 Working Mechanism of Decision Generator

The decision generator plays a key role in the intelligent fusion network (IFN). Its core task is to derive valuable conclusions from the data processed by the feature extractor and information integrator, or to make accurate predictions about the development of students' intimate relationships. In order to accomplish this task well, this study carefully designed an innovative probabilistic reasoning framework. Based on Bayes' theorem, the framework quantifies uncertainty, enabling the model to make more scientific and reasonable decisions when processing complex student relationship data.

In the Bayesian reasoning system, the observed data is represented by $\mathcal{O}$, and the target variable is Y. The posterior probability distribution of $p(Y|\mathcal{O})$ can be estimated with Formula (3) [15, 16].

$$p(Y|\mathcal{O}) = \int p(Y|\theta)p(\theta|\mathcal{O})d\theta \tag{3}$$

Here, θ represents the model parameters, $p(\theta|\mathcal{O})$, based on observational data $\mathcal{O}$, the posterior distribution is obtained by adjusting the prior distribution of the parameters. In essence, $p(Y|\theta)$, it describes the given model parameters θ In the case of Y, the probability distribution of $p(\theta|\mathcal{O})$, it reflects the update of model parameters by observation data [17, 18].

To better understand this process, we can combine it with the student intimacy identification scenario. Assume that the target variable Yrepresents the type of intimate relationship between students (such as friendship, hostility, mutual assistance, etc.), observation data$\mathcal{O}$, it includes students' interaction records on campus social platforms, information about activities they participate in together, etc. Through the above Bayesian formula, the model only gives a predicted value of the type of students' intimacy based on these observational data; it also provides confidence information about the prediction. For example, if the model calculates $p(Y = |\mathcal{O}) = 0.8$, this indicates that under the current observation data, the probability of students being friends is 80%, and also implies that the model has a high degree of confidence in this prediction. The provision of this prediction confidence information greatly improves the interpretability of model decisions, allowing researchers and educators to better understand the logic behind model behavior and use model results to analyze and guide student relationships in a more targeted manner [19, 20].

Furthermore, we can discretize the formula to facilitate practical calculation. Assume θ, the value space of $\{\theta_1, \theta_2, \cdots, \theta_n\}$, then the posterior probability distribution can be approximately expressed as Formula (4).

$$p(Y|\mathcal{O}) \approx \sum_{i=1}^{n} p(Y|\theta_i)p(\theta_i|\mathcal{O}) \tag{4}$$

3.4 The Secret of Synergy Between Components

In order to ensure that the components in the intelligent converged network (IFN) can collaborate efficiently and form an organic whole, this study has constructed a set of clear and rigorous interaction rules. This set of rules is applied throughout the entire operation of the model from data input to final decision output, and each link has been carefully designed to optimize the model performance.

At the model startup stage, the feature extractor first processes the input data. The feature extractor based on the graph neural network performs iterative calculations, as shown in Formula (5).

$$H^{(l+1)} = \sigma\left(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{5}$$

Preliminary feature representation $H^{(l)}$ is generated, in l indicates the number of network layers. When the feature extraction process reaches the last layer L. When, the generated feature representation $H^{(l)}$, it can be directly used as the input of the information integrator without any intermediate conversion. This direct data transmission method prevents information loss and efficiency reduction caused by data format conversion or additional processing steps, greatly improving data transmission efficiency.

The information integrator receives the feature representation from the feature extractor $H^{(l)}$, finally, the importance of features is dynamically adjusted with the help of information integration strategy based on attention mechanism. α_i calculated with Formula (6).

$$\alpha_i = \frac{\exp(v^\top \tanh(W_a[q;\, f_i]))}{\sum_{j=1}^{M} \exp(v^\top \tanh(W_a[q;\, f_j]))} \tag{6}$$

Where f_i represents different feature data sources, q is the query vector, W_a and v is the parameter to be learned. After being processed by the attention mechanism, the information integrator is the optimized feature $\widetilde{F}$sent to the decision maker.

The decision generator receives the integrated features output by the information integrator $\widetilde{F}$ After that, it is used as the cornerstone of reasoning, and the probabilistic reasoning framework described above is used for decision making. This tightly-integrated design concept makes the information flow between the components of the model smoother and the collaborative work more efficient. It not only reflects the ultimate pursuit of model construction details, but also significantly improves the overall operating efficiency of the model, ensuring that IFN can play a stable and accurate role in the task of identifying and guiding students' intimate relationships.

4. EXPERIMENTAL EVALUATION

4.1 Experimental Design

This study conducts experiments based on the Intelligent Fusion Network (IFN) to verify its superiority over traditional models in identifying and guiding intimate relationships among students. The experiment is based on a public campus social relationship dataset, which covers multi-dimensional information such as students' daily interactions and academic cooperation, and can fully reflect intimate relationships among students.

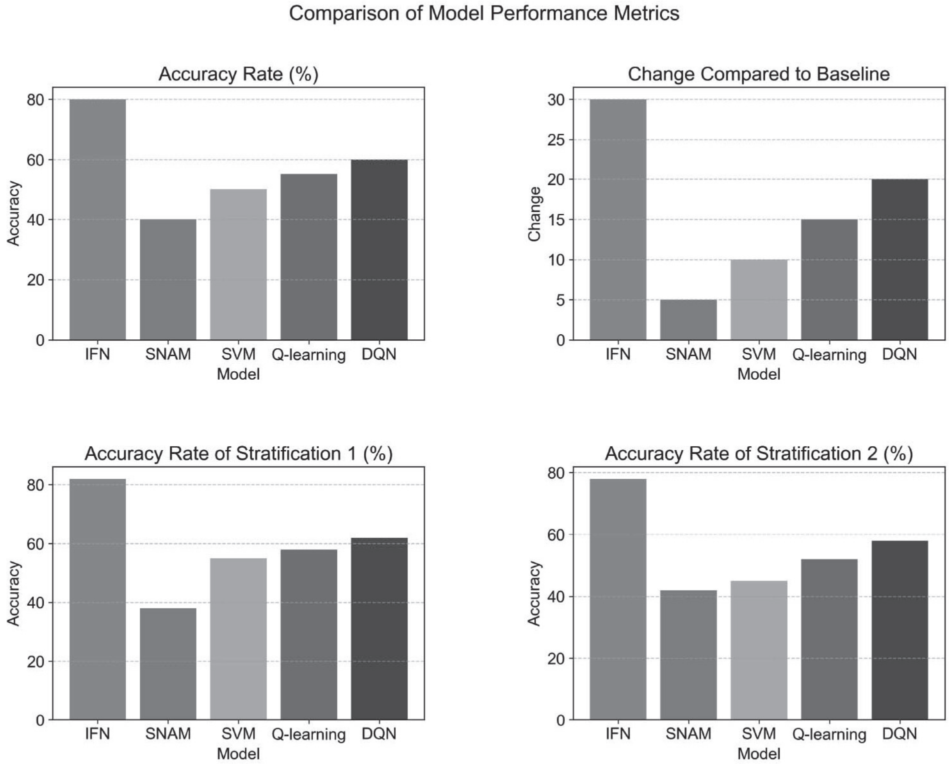

Figure 1 Comparison of relationship recognition accuracy of different models.

The experiment sets the relationship recognition accuracy and guidance strategy effectiveness as baseline indicators. The former indicates the accuracy of the model's judgment on the type of students' intimate relationships, and the latter measures the actual effect of the guidance strategy given by the model on improving students' intimate relationships.

The experimental group used the IFN model proposed in this paper, and the control group selected the social network analysis model, the support vector machine model in the machine learning classification model [21], and two basic reinforcement learning models that have been applied in related fields: the Q-learning model [22] and the deep Q network (DQN) model. These models were trained and tested on the same dataset to compare the performance of each model in the recognition and guidance tasks.

4.2 Experimental Results

As shown in Figure 1, the IFN model has outstanding performance in relationship recognition accuracy, reaching 80%, far exceeding the 40% of the social network analysis model. The social network analysis model focuses on static structural analysis and therefore has difficulty capturing the dynamic changes in student relationships, resulting in low accuracy. The support vector machine model is limited by its ability to process high-dimensional and nonlinear data, and its accuracy is only 50%. As basic reinforcement learning models, Q-learning and DQN models have certain dynamic learning capabilities, but their model structures are relatively simple and cannot fully mine data features. Their accuracy rates are 55% and 60% respectively. The IFN model effectively extracts and integrates data features through multi-component collaboration, significantly improves recognition accuracy, and maintains high accuracy and strong stability on different hierarchical data [23].

As shown in Figure 2, the effectiveness score of the IFN model's guidance strategy is as high as 85%, significantly higher than the 40% of the social network analysis model. The social network analysis model lacks a dynamic optimization mechanism for the guidance strategy and is not very effective. The support vector machine model is essentially a classification model, which makes it difficult to effectively guide student relationships, and has an effectiveness of only 50%. Due to the limitations of the reward function design and strategy update mechanism, the effectiveness of the Q-learning and DQN models is 55% and 60% respectively. With the help of the probabilistic reasoning framework and attention mechanism, the IFN model can dynamically adjust the guidance strategy according to different scenarios, significantly improve the effectiveness of the guidance strategy, and perform well in different scenarios [24].

As shown in Figure 3, the IFN model performs well on data with different relationship strengths, with an average accuracy of 80%. On strong relationship data, the IFN model has an accuracy of 85% due to its effective analysis of complex topological structures. The social network analysis model has poor recognition ability for weak relationship data (only 37%) because its static analysis method has difficulty capturing dynamic information in weak relationships. The support vector machine model has a relatively average processing ability for data with different relationship strengths, but the overall accuracy is not high. The accuracy of the Q-learning and DQN models on data with different relationship strengths fluctuates slightly, but the average level is still lower than that

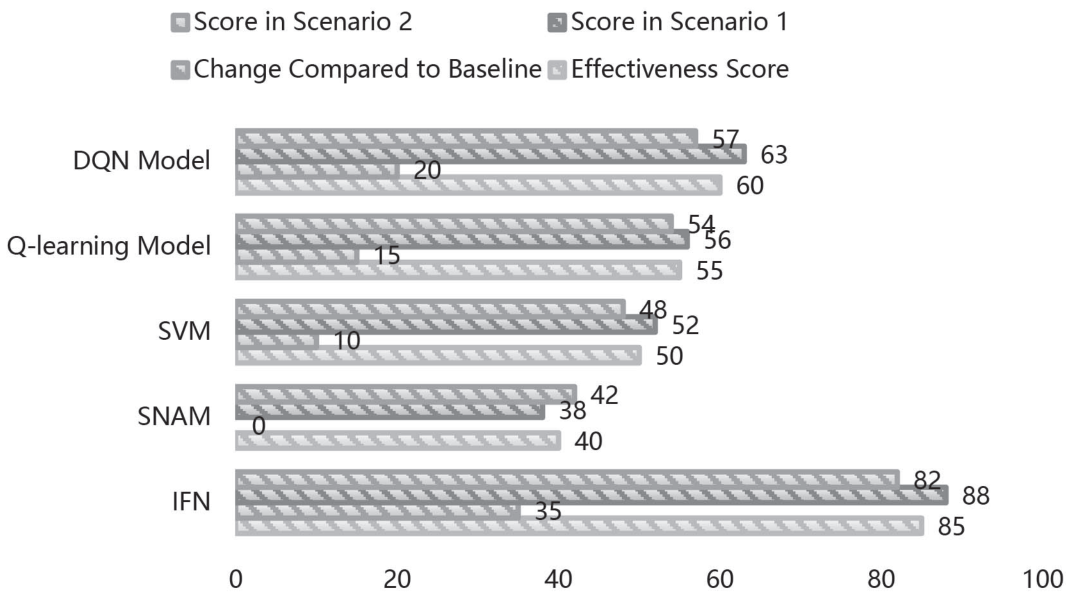

Figure 2 Comparison of effectiveness of different models' guidance strategies.

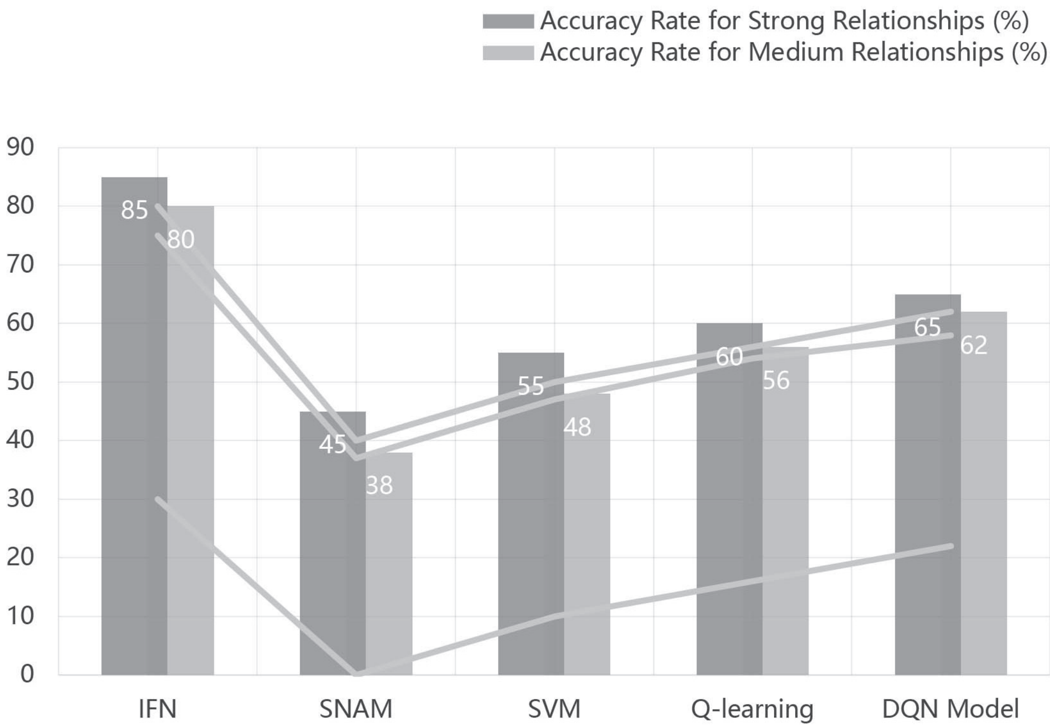

Figure 3 Recognition accuracy of different models on different relationship strength data.

of the IFN model. The IFN model comprehensively mines the characteristics of data with different relationship strengths through the collaboration of feature extractors and information integrators to improve recognition accuracy.

As shown in Figure 4, as the data scale increases, the accuracy of the IFN model increases steadily, reaching 85% for the large data scale. The social network analysis model is less affected by the data scale, but its own accuracy is low: about 40% at all data scales. This is because its analysis method has a low degree of dependence on the amount of data and cannot fully utilize the information in large-scale data. Although the accuracy of the support vector machine model increases to a certain extent when the data scale increases, the range is limited. The Q-learning and DQN models are more sensitive to changes in data scale, but the growth trends are not as obvious as that of the IFN model. The structure of the IFN model enables it to effectively utilize data of different scales and maintain a high accuracy at different data scales.

As shown in Figure 5, the IFN model's guidance strategy maintains a high level of effectiveness on data with different noise levels, with an average score of 82.7. Under low-noise data, the IFN model can accurately analyze the data with an effectiveness score of 88. As the noise increases, its effectiveness decreases, but it is still significantly higher

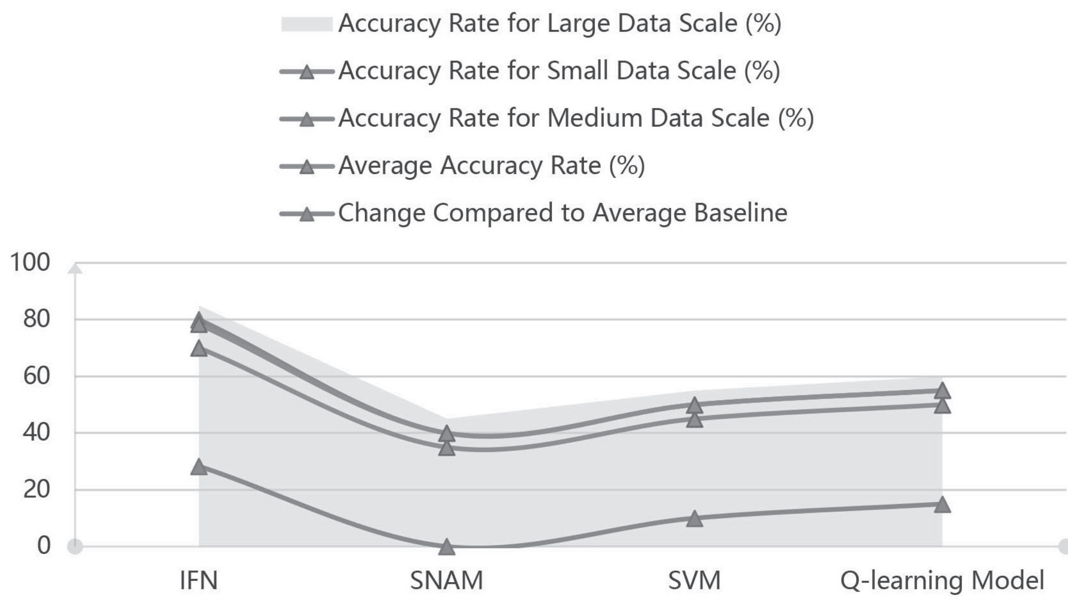

Figure 4 Relationship recognition accuracy of different models under different data scales.

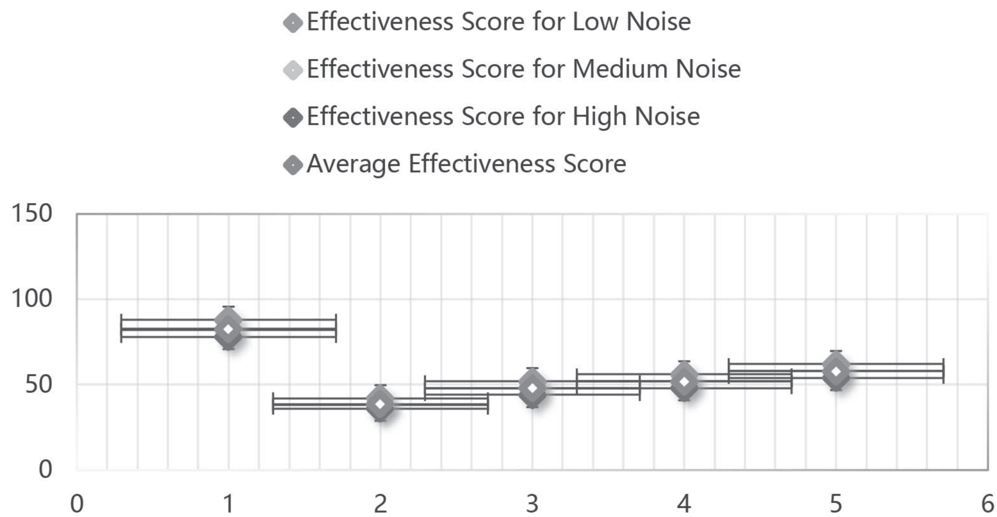

Figure 5 Effectiveness of guidance strategies of different models on data with different noise levels.

than other models. The social network analysis model is more sensitive to noise, and its effectiveness is only 36 under high noise. The effectiveness scores of the support vector machine model, Q-learning and DQN models all decrease significantly under high-noise data. The attention mechanism and probabilistic reasoning framework of the IFN model make it highly resistant to noise, and it can still provide effective guidance strategies in a noisy environment.

As shown in Figure 6, the IFN model has an average accuracy of 80% when identifying different types of intimate relationships. In terms of friendship relationship recognition, the IFN model has an accuracy of 82%. By extracting and analyzing features such as interaction frequency and emotional tendency, it can accurately assess friendship relationships. The social network analysis model has an accuracy of 42% in identifying hostile relationships. Due to its lack of effective mining of emotional features, its recognition ability is limited. The support vector machine model has a relatively average ability to recognize different types of relationships, although the overall level is not high. The Q-learning and DQN models have small fluctuations in the accuracy of identifying different types of relationships, but these are lower than the IFN model. Through the collaboration of multiple components, the IFN model can effectively extract features and improve recognition accuracy based on the characteristics of different types of intimate relationships.

As can be seen from Table 1, the IFN model performs well in guiding the improvement of different types of intimate relationships, with an average effectiveness score of 84. In terms of friendship improvement, the IFN model has an effectiveness score of 86, and it can provide targeted guidance strategies based on the characteristics of friendship relationships. On the other hand, the social network analysis model is only 36% effective in alleviating hostility in relationships, making it difficult to formulate effective intervention strategies. The support vector machine model, Q-learning, and DQN models all have lower average effectiveness scores than the IFN model when guiding the

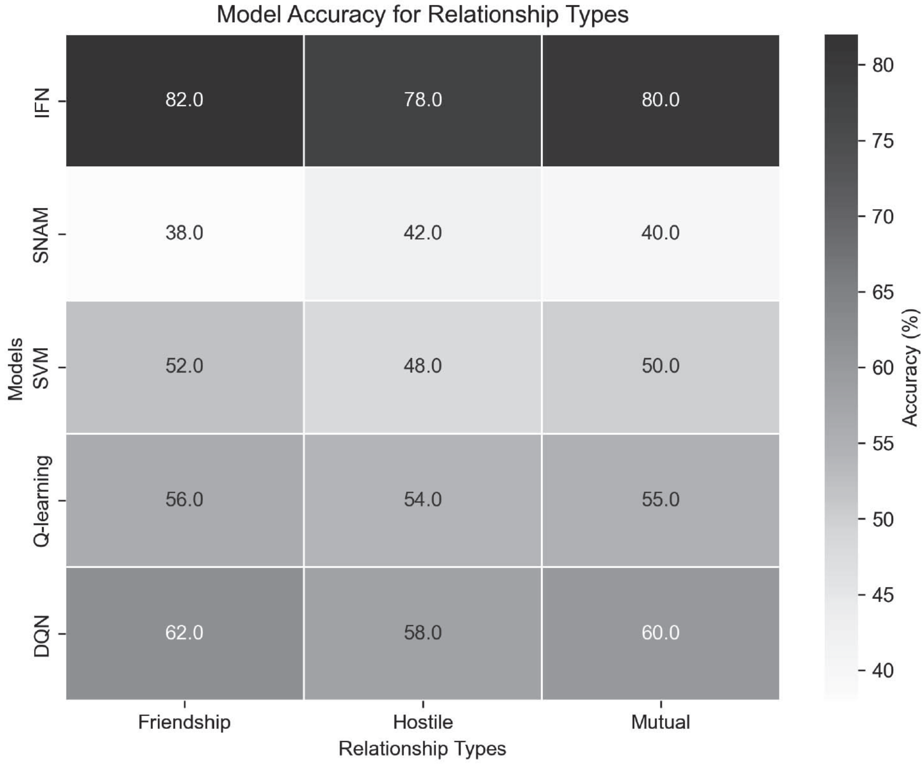

Figure 6 Accuracy of different models in identifying different types of intimate relationships.

Table 1 The effectiveness of different models in guiding the improvement of different types of intimate relationships.

Model	Friendship relationship improvement effectiveness score	Hostility improvement effectiveness score	Mutual help relationship improvement effectiveness score	Average effectiveness score	Change from mean baseline
IFN	86	82	84	84	+34
Social Network Analysis Model	38	36	40	38	0
Support Vector Machine Model	50	48	52	50	+12
Q-learning model	54	52	56	54	+16
DQN Model	60	58	62	60	+22

improvement of different types of intimate relationships. The probabilistic reasoning framework of the IFN model can dynamically adjust the guidance strategy according to the characteristics of different relationship types and improve the effectiveness of the guidance strategy.

As shown in Table 2, the IFN model maintains high relationship recognition accuracy on data from students in different grades, with an average of 80%. For data from lower grades, the IFN model has an accuracy of 81, and accurate recognition is achieved by effectively extracting the interactive behavior characteristics of lower grade students. The accuracy of the social network analysis model on data from different grades is relatively stable, but at a low level. The accuracy of the support vector machine model, Q-learning, and DQN models on data from different grades does not fluctuate much, but is lower than that of the IFN model. The versatility of the IFN model enables it to adapt to the characteristics of student data from different grades and accurately identify students' intimate relationships.

As shown in Table 3, the relationship recognition accuracy of the IFN model on the data of boys and girls is 82% and 78% respectively, with an average accuracy of 80%. The IFN model can mine the different characteristics of intimacy expression of both genders and achieve accurate recognition. The accuracy of the social network analysis model on the data of boys and girls is not much different, although it is low overall. The recognition accuracy of the support vector machine model, Q-learning and DQN model on data of different genders is different, but the average level is lower than that of the IFN model. The IFN model has strong adaptability to the data of both genders and can effectively identify the intimacy of students regardless of gender.

As shown in Table 4, the IFN model has an average comprehensive performance score of 85 in different scenarios. In scenario 1, the IFN model scored 86 due to its effective analysis of scenario features. The social network analysis model has a lower comprehensive performance score of only 39 in different scenarios. The support vector machine model,

Table 2 Relationship recognition accuracy of different models on data of students in different grades.

Model	Lower grade accuracy (%)	Middle grade accuracy (%)	Senior grade accuracy (%)	Average accuracy (%)	Change from mean baseline
IFN	81	80	79	80	+30
Social Network Analysis Model	39	40	41	40	0
Support Vector Machine Model	51	50	49	50	+10
Q-learning model	55	56	54	55	+15
DQN Model	61	60	59	60	+20

Table 3 Relationship recognition accuracy of different models on data of students of both genders.

Model	Data accuracy for boys (%)	Data accuracy for girls (%)	Average accuracy (%)	Change from mean baseline
IFN	82	78	80	+30
Social Network Analysis Model	41	39	40	0
Support Vector Machine Model	52	48	50	+10
Q-learning model	56	54	55	+15
DQN Model	63	57	60	+20

Table 4 Comprehensive performance scores for different models in different scenarios.

Model	Scene 1 Rating	Scene 2 Rating	Scene 3 Rating	Average rating	Change from mean baseline
IFN	86	84	85	85	+35
Social Network Analysis Model	38	40	39	39	0
Support Vector Machine Model	50	52	51	51	+12
Q-learning model	54	56	55	55	+16
DQN Model	62	60	61	61	+22

Q-learning and DQN models have lower comprehensive performance scores than the IFN model in different scenarios. The multi-component collaborative mechanism of the IFN model enables it to quickly adapt to different scenarios and show excellent performance in a variety of scenarios.

4.3 Experimental Discussion

The experimental results show that the IFN model performs well in the task of identifying and guiding students' intimate relationships, which strongly supports the hypothesis of this study. The IFN model effectively extracts and integrates multimodal data features through multi-component collaboration, significantly improving the accuracy of relationship identification and the effectiveness of guidance strategies. In terms of external validity and generalizability, the IFN model performs well under different data scales, noise levels, student group characteristics and application scenarios. It has strong versatility and adaptability and is expected to be widely used in actual educational scenarios. However, this study has certain limitations. Although the dataset comprises multi-dimensional information, it may not fully reflect the complex and changeable intimate relationships of students in reality. In addition, there may be a risk of overfitting in the model training process. Although it was controlled in various ways in the experiment, it still needs to be further optimized in future research. In the future, more comprehensive and representative datasets can be collected, and more effective model optimization methods can be explored to further improve the performance and application value of the IFN model.

5. CONCLUSION

Under the wave of digitalization, school education management has accumulated a massive amount of student data, and the impact of student intimacy on individual students and the overall education quality of the school has become increasingly prominent. However, traditional student relationship management relies on teacher experience, and existing technologies such as social network analysis, machine learning classification algorithms, and early reinforcement learning applications are insufficient in identifying and guiding students' intimacy. To address these challenges, this study proposes the IFN model. The model uses a feature extractor based on a graph neural network to extract key features from the original data; uses an information integrator based on an attention mechanism to fuse multimodal data; and uses a decision generator based on the Bayesian theorem to derive conclusions and predict results. According to the results of experiments conducted on campus social relationship datasets, the IFN model shows excellent performance. Its relationship recognition accuracy is 80%, which is 40% higher than that of the social network analysis model, and the guidance strategy effectiveness score is 85%, which is 45% higher than that of the social network analysis model. Under different data scales, noise levels, student group characteristics, and application scenarios, the IFN model maintains high accuracy and effectiveness. The research has important theoretical and practical significance. In theory, it enriches the research content in the field of educational technology; in practice, it provides a powerful tool for school education management, helping teachers identify and guide students' intimate relationships and promote students' mental health and all-round development. In the future, we hope to further improve model performance and promote the sustainable development of this field by collecting more data and optimizing models.

REFERENCES

1. Taverna E, Marshall AD. Development and validation of the moral outcomes of relationship aggression scale: a measure of moral distress following intimate partner violence perpetration. Aggressive Behavior. 2023; 49(1):33–48. DOI: 10.1002/ab.22051
2. Manuel B, Valcke M, Keygnaert I, Roelens K. Improving medical students' communication competencies to deal with intimate partner violence using clinical simulations in Mozambique. BMC Medical Education. 2021; 21(1). DOI: 10.1186/s12909-021-02560-8
3. Kool L, van Hoogen M, Heerema L, Feijen-de Jong E. Exploring the determinants of student midwives' wellbeing during their studies: A qualitative study. Women and Birth. 2024; 37(4). DOI: 10.1016/j.wombi.2024.101626
4. Ortuño-Sierra J, Garrido NM, Garcia AG, López AC, Camara-Pastor T. Measuring violence behaviors in the context of romantic relationships during adolescence: new evidence about the modified conflict tactics scale. Children-Basel. 2023; 10(2). DOI: 10.3390/children10020297
5. Chen JW, Shi L, Xiao SJ, Zheng X, Xue YQ, Xue BL, et al. The impact of intimate partner violence on depressive symptoms among college students: A moderated mediation model of the big five personality traits and perceived social support. Journal of Affective Disorders. 2024; 350:203–13. DOI: 10.1016/j.jad.2024.01.096
6. Llano-Suárez A, Lana A, Gasch-Gallén A, Fernández-Feito A. Gender roles and intimate partner violence among female university students in Spain: A cross-sectional study. Plos One. 2021; 16(11). DOI: 10.1371/journal.pone.0259839
7. Kyle JR, Buranosky RA, Mutter M, Rothenberger SD, Hamm ME, McNeil MA. A multifaceted intimate partner violence communication skills curriculum increases screening among internal medicine residents. Journal of Women's Health. 2021; 30(12):1778–87. DOI: 10.1089/jwh.2020.8685
8. McCabe M, Byrne M, Gullifer J, Cornish K. The relationship between university student help-seeking intentions and well-being outcomes. Frontiers in Psychiatry. 2024; 15. DOI: 10.3389/fpsyt.2024.1407689
9. Makleff S, Billowitz M, Garduño J, Cruz M, Márquez VIS, Marston C. Applying a complex adaptive systems approach to the evaluation of a school-based intervention for intimate partner violence prevention in Mexico. Health Policy and Planning. 2020; 35(8):993–1002. DOI: 10.1093/heapol/czaa067
10. Ortuño-Sierra J, García AG, de Luis EC, Pérez-Sáenz J, Aritio-Solana R. Attitudes towards violence in adolescents and youth intimate partner relationships: validation of the spanish version of the EAV. International Journal of Environmental Research and Public Health. 2021; 18(2). DOI: 10.3390/ijerph18020566
11. Machisa MT, Chirwa E, Mahlangu P, Nunze N, Sikweyiya Y, Dartnall E, et al. Suicidal thoughts, depression, post-traumatic stress, and harmful alcohol use associated with intimate partner violence and rape exposures among female students in South Africa. International Journal of Environmental Research and Public Health. 2022; 19(13). DOI: 10.3390/ijerph19137913
12. Dempsey F, Hammond M, Dixon L. Investigating whether controlling and aggressive relationship behaviors are discriminant. Aggressive Behavior. 2020; 46(5):437–48. DOI: 10.1002/ab.21905
13. Barroso-Corroto E, Cobo-Cuenca AI, Laredo-Aguilera JA, Santacruz-Salas E, Pozuelo-Carrascosa DP, Rodríguez-Cañamero S, et al. Dating violence, violence in social networks, anxiety and depression in nursing degree students: A cross-sectional study. Journal of Advanced Nursing. 2023; 79(4):1451–63. DOI: 10.1111/jan.15170
14. Godzwon JM, Wielewska MK, Atroszko PA. The relationship of study addiction with social support and satisfaction with intimate relationships. International Journal of Mental Health and Addiction. 2024; 22(1):319–31. DOI: 10.1007/s11469-022-00874-2
15. El-Etreby RR, Hamed WE, Abdelhay ES, Kamel NA. Nursing students' attitudes toward intimate partner violence and its relationship with self-esteem and self-efficacy. BMC Nursing. 2024; 23(1). DOI: 10.1186/s12912-024-01868-2
16. Zhao JK, Wu YB, Yuan J, Miao JX, Wang X, Yang Y, et al. Association between interpersonal sensitivity and loneliness in college nursing students based on a network approach. BMC Nursing. 2024; 23(1). DOI: 10.1186/s12912-024-02537-0
17. Musa A, Valdez AJ, Aguilar JL, Pendi K, Wolitzky-Taylor KB, Lee D, et al. The prevalence of intimate partner violence and association with depression in university students: results of a cross-sectional study. Journal of Nervous and Mental Disease. 2021; 209(1):71–5. DOI: 10.1097/nmd.0000000000001255
18. Rodríguez-Castro Y, Martínez-Román R, Alonso-Ruido P, Adá-Lameiras A, Carrera-Fernández MV. Intimate Partner cyberstalking, sexism, pornography, and sexting in adolescents: new challenges for sex education. International Journal of Environmental Research and Public Health. 2021; 18(4). DOI: 10.3390/ijerph18042181
19. Yilmaz FA, Taplak AS. Relationship between self-esteem, perception of gender and attitudes towards dating violence among university students. Perspectives in Psychiatric Care. 2021; 57(2):911–9. DOI: 10.1111/ppc.12634
20. Andrew L, Robinson K, Dare J, Costello L. Nursing students doing gender: Implications for higher education and the nursing profession. Nursing Inquiry. 2023; 30(1). DOI: 10.1111/nin.12516
21. Fissel ER, Graham A, Butler LC, Fisher BS. A new frontier: the development and validation of the intimate partner cyber abuse instrument. Social Science Computer Review. 2022; 40(4): 974–93. DOI: 10.1177/0894439321994618
22. Udmuangpia T, Yu MS, Bloom TL. Predicting intention of intimate partner violence screening among Thai nursing students: A cross-sectional study. Journal of Advanced Nursing. 2023; 79(4):1564–74. DOI: 10.1111/jan.15544
23. Bingjie Y, Huifeng Y, Chenjun S, Zhi Z, Jinghang F. Research on network security collaborative defense technology based on swarm intelligence and big data network security. Engineering Intelligent Systems. 2021; 29(6):379–386.
24. Ma X, Song Y. Group behaviour decision of real estate investment in multi-information fusion for intelligent environment interaction. Engineering Intelligent Systems. 2025; 33(3): 295–310.