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Emotion Analysis and Knowledge Reasoning Fusion Framework for Long-Term Deep Care by Elderly Care Robots

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Abstract The aggravation of population aging makes the demand for elderly care expanding. In this paper, we propose an integrated care model based on deep learning to build an intelligent service robot system for elder care organizations by integrating sentiment analysis and knowledge reasoning techniques. The model is driven by the dynamic needs in long-term care scenarios, and two modules are innovatively designed. In the sentiment analysis module, multimodal sensors (facial expression, audio state, textual content) and graph attention networks are integrated, and global contextual information is modeled on these features to identify long-distance emotional dependencies of the elderly. In the knowledge inference module, graph representation learning is combined with knowledge graph temporal inference to construct an inference model to speculate the care needs of the elderly. The experiment shows that after the system performs long-term service, the depression condition of the elderly is significantly improved, and the nursing care safety risk perception shows a significant difference from that before the system is used (P<0.001). The integrated care model studied in this paper provides a practical technical solution to the problem of aging care resource shortage.

Index Terms Deep learning, multimodal sensors, knowledge graph, service robot, elder care

I. Introduction

In recent decades, as China's population has been aging at an accelerating rate and the family structure has changed dramatically, the issue of elderly care has become more and more prominent. The question of how to solve the problem of health care for the elderly and improve their quality of life has become a social problem that needs to be solved urgently in China.

The traditional single model of children caring for their parents has been unsustainable in modern society, and in the face of the reality of shortage of human resources for the elderly, the introduction of care robots in the practice of elderly care, so that they take part of the care labor, has become an important way of contemporary and future practice of elderly care [1]-[4]. At the same time, the high-tech content of care robots can optimize the interaction, so that the elderly can experience the changes of the times, and to a certain extent can dilute the generation gap between the elderly and their children, and harmonize family relations [5-7]. This new type of elderly care can not only effectively alleviate the pressure of family care, but also improve the quality of life and happiness of the elderly [8], [9]. At present, robot-centered elderly care is increasingly becoming an important means to alleviate China's elderly care problems, improve the quality of care, and meet the needs of the elderly for a better life [10-12]. Nursing service robots have been gradually promoted and applied in hospitals, nursing homes and other institutions.

On the basis of ensuring the basic needs of the elderly, it should also pay attention to the psychological health of the elderly and improve their quality of life [13]. In the modern nursing model, the psychological and emotional factors of the elderly have become the focus of nursing care, and the design of nursing robots must deeply consider this aspect [14], [15]. After retirement, the circle of life and social circle of the elderly is reduced, and the lifestyle changes are large, but most of them are bland and monotonous, and often produce negative emotions such as emptiness, loneliness, and being left out [16]-[18]. Prolonged negative emotions in turn cause deep remorse in the elderly, which is very harmful to the spirit of the elderly, and at the same time has a serious impact on the already gradually declining physical function and memory capacity of the elderly [19]-[21]. Therefore, the positioning of nursing robot products should not be just as a tool to assist the elderly in completing a certain part of their labor needs during caregiving events, but rather an innovative definition and design of nursing functions based on a full perception of the emotional needs of the elderly [22]-[25].

According to Maslow's hierarchy of needs theory, needs can be broadly classified into physiological needs, safety needs, emotional and belonging needs, respectability needs, and self-actualization needs [26]. Physiological needs and safety needs, as the basic needs of the elderly to maintain their daily lives, require nursing robots to assist the elderly in solving some of these problems, and scholars have carried out relevant research on this. Martinez-Martin, E. et al. described the advantages shown by integrated robots in the field of caregiving in societies with aging populations, with a wide range of functions, including healthcare, daily assistance, and self-management, for the care of the elderly [27]. Johnson, M. J. et al. discussed the design requirements of mobile service robots for elderly care and showed that care robots should fulfill task objectives such as reminding, companioning, hydration, and fetching assistance to meet the needs of elderly people in their daily lives on a cost-controllable basis [28]. Ahuja, G. et al. summarized the daily tasks in elderly care that require robotic assistance to be delegated to a robot to provide elderly life care with the aim of designing a mobile robot for assistive and nursing care with personalized and customized features [29].

However, in addition to physiological level needs, older people also need to satisfy emotional level needs such as social relationship building, emotional regulation, and daily workplace interactions, so emotional factors can be used as another starting point for the design of care robots.Aronsson, A. S. analyzes the phenomenon of emotional attachment generated by social robots in the field of care for older people, and argues that the introduction of sentiment analysis technology will not produce the same experience as the same experience as human interactions, but will result in new ways of relating and interacting between older people, caregivers and family members [30]. Chen, N. et al. examined the feasibility of social robots to fulfill the companionship needs of the elderly in different life situations, and made an important contribution to the construction of a home care system that meets the emotional needs of the elderly [31]. Cobo Hurtado, L. et al. have built a care platform that can provide different services to the elderly, which can effectively stimulate cognition and foster an emotional connection between the elderly and the robot through a bimodal form of interaction with mental state detection [32]. Kok, C. L. et al. showed that social robots can enhance interaction with older adults to reduce loneliness in their lives while promoting mental and physical health, and that their application in healthcare organizations can effectively improve the quality of life of older adults [33]. Kiran, A. et al. proposed an AI-enhanced geriatric care robot that, in addition to personalized care interventions and health monitoring, promotes meaningful social activities and positively improves the mental health of older adults through a loneliness assessment tool [34].

In this paper, an integrated care model combining sentiment analysis and knowledge reasoning is designed for application in a service robot system. Considering the need for long-term care for the elderly, in the sentiment analysis module, a context information fusion network with a self-attention mechanism and a graph attention network is used to capture the context information of the current discourse, model the context information by applying a self-attention operation to the modality, and then judge the important features of the highlighted anchored discourse by a graph attention neural network, which is used to balance the interdependence of the context and the anchoring vectors. In the knowledge inference module, the multi-relational graph structure encoder is designed for the neighbor structure information in graph representation learning. And the attention mechanism is introduced into the temporal encoder to design the model temporal inference algorithm to infer the care needs of the elderly. The application performance of the model in this paper is tested by comparing it with the baseline model for sentiment analysis and knowledge inference. After the integrated care model is applied to the service robot system, the change in the depression level of the elderly and the cognitive mastery of care safety risks are counted to judge the actual use effect of the model.

II. Deep learning-based model for integrated care

With the continuous development of sensor technology and artificial intelligence technology, the ability of service robots to perceive and judge the external environment is constantly improving. Among them, visual perception, tactile perception, audio perception, autonomous navigation, autonomous grasping, and other functions have been applied in a large number of service robots [35]. The use of service robots in elderly care organizations can effectively reduce the work pressure of caregivers and improve the quality of life of the elderly. In order to achieve personalized and efficient services, this paper designs a deep learning-based integrated care model in the context of long-term care, and the overall framework of the model is shown in Figure 1. The model mainly contains two modules of sentiment analysis and knowledge reasoning.

II. A.Sentiment analysis module

Service robots cannot understand the emotional appeal of the elderly based on just one sentence or one expression during long-term care. In order to accurately understand and process complex emotional expressions, this chapter proposes a multimodal sentiment analysis model using graph-attention neural networks, with the aim of capturing and utilizing the intricate contextual connections between different modalities for analysis, and improving the accuracy and depth of multimodal sentiment analysis.

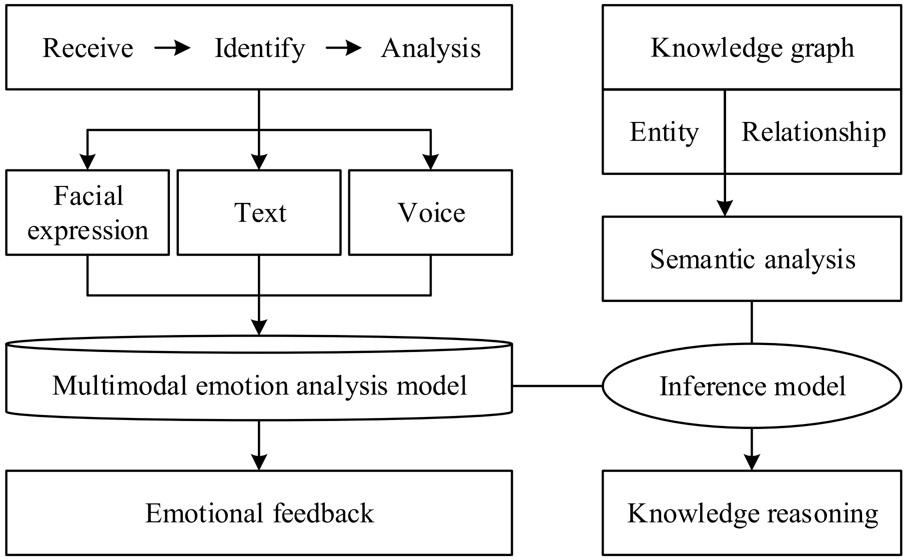


Figure 1: Comprehensive nursing model framework

II. A. 1) Problem definition

In this study, the dataset analyzed is derived from various types of video content collected from TV drama episodes and online video platforms. The three modalities of data contained in the videos are represented as a whole by $M = \{T, A, V\}$, using T for text modality, A for audio modality, and V for video modality, where $|M|$ is the length of the sentiment analysis video in the dataset. In this dataset, the video content is subdivided into a series of consecutive dialog segments, where each segment constitutes a more independent linguistic unit. The sequence of consecutive segments is shown in Equation (1):

$$x_i^M = \left[X_{i,1}^M, X_{i,1}^M, \dots, X_{i,s_j}^M\right] \tag{1}$$

where X_i, s_j denotes the content of the s_jrd clip contained in the i nd video, where s_j denotes the number of words in the content of each video dialog clip, and M represents different modalities. Given a piece of multimodal information, in this paper, we use $I_i = \{I_i^T, I_i^T, I_i^V\}$, which represents the unimodal features after extraction by the pre-trained model. The extraction is shown in Eqs. (2) to (4):

$$T_{l^i} = RoBERTa(X_{i,1}^T, X_{i,1}^T, \dots, X_{i,s_i}^T) \tag{2}$$

$$V_{l^i} = CLIP-VE_{finetune}(X_{i,1}^V, X_{i,1}^V, \dots, X_{i,s_i}^V) \tag{3}$$

$$A_{l^i} = OpenSmile(X_{i,1}^A, X_{i,1}^A, \dots, X_{i,s_i}^A) \tag{4}$$

where $CLIP-VE_{finetune}$ denotes the visual coder of the fine-tuned CLIP model. In order to facilitate the improved self-attention mechanism and the improved contrastive attention mechanism, this paper extracts not only the word-level feature information $T_{l^i}, A_{l^i}, V_{l^i}$ of the different features of the multimodality, but also its sentence-level feature information $T_{s^i}, A_{s^i}, V_{s^i}$.

II. A. 2) Multimodal Sentiment Analysis Models

Current multimodal sentiment analysis methods lack complete modeling of contextual information and adequate extraction of hidden information in terms of facial expressions, audio states, and textual content. Service robots cannot recognize emotions based on the prevailing context alone when assisting long-term care in elderly care facilities, but rather must fully incorporate recent emotional expressions to make comprehensive judgments. In this regard, the graph attention neural network multimodal sentiment analysis model proposed in this subsection addresses this issue by adequately modeling multimodal contextual information through graph structure and attention mechanisms.

(1) Modeling Contextual Information in Graph Attention Neural Networks

The graph attention structure, similar to the traditional graph structure, is built on top of a collection of nodes and a collection of connected edges between these nodes to form a specific form of data organization, with the nodes representing each sample of video footage and the edges representing the temporal relationships between the samples. Because the character movement expression etc. in the video carries the timing information before and after the moment, the before and after moment emotions in the video are highly correlated. This before-and-after moment connection can be structurally mapped into a graph structure relationship, and the graph attention structure is automatically focused on the neighboring node that is most relevant to the current node's emotion by learning the dynamic attentional weights, as shown in the formula in (5). In this study, node set $G^v \in R^{N\times f}$ consists of multimodal sentiment features extracted by the self-attention mechanism, where N is the number of neighboring samples, and f represents the multimodal sentiment feature dimension of each sample obtained through the self-attention mechanism. To delineate these nodes, the cosine similarity method of metric learning is used, and the neighbor matrix A is used to specify the connection relationship between nodes, i.e., the edge set information G^e, through the attention mechanism:

$$Sim_a tt = sigmoid(cos\_sim(v_i, v_j) \cdot (att(v_i) \cdot att(v_j))) \tag{5}$$

where i and j represent the multimodal sentiment feature vectors of the i rd and j th neighboring samples, and cos_sim represents the similarity result between these vectors, measured using cosine similarity. $att(v_i)$ is used to quantify the attention weights of vector v_i when the similarity weighted value $Sim\_att \geq 0.75$. In the adjacency matrix A, the corresponding element $a_{i,j}$ is set to 1. When $sim\_att < 0.75$, the corresponding element $a_{i,j}$ is set to 0.

(2) Graph Attention Neural Network Model

After the architecture of the graph attention network is established, this study proceeds to develop the corresponding model to perform the sentiment analysis task. This paper details how to use graph structure data as input to the graph attention network and implement attention weighting on this data. The implementation of the graph attention mechanism for any selected node in the graph structure is handled by calculating the attention coefficient between all neighboring nodes of the target node, which indicates the importance of the neighboring nodes to the target node, and then weighting the neighboring nodes by feature aggregation to obtain the new representation of the target node, and the formula for the graph attention operation is shown in (6):

$$H^{l+1} = \sigma\left(D^{-\frac{1}{2}}(A+I)D^{-\frac{1}{2}}H^l W^l\right) \tag{6}$$

where the degree matrix D is a negative diagonal matrix with each value on the diagonal being $\Sigma_j a_{i,j}$, where $a_{i,j}$ denotes the elements of row i and column j of the similarity adjacency matrix A, H^l denotes the output of the l th layer of the graphical attention neural network, and $H^0 = self-Attention(A,V,T)$, where matrix H^0 contains the feature vectors generated by the self-attention mechanism These vectors are affected by the parameters of the trainable linear transformation W^l, and l denotes the number of layers of the graphical attention neural network. By adding multiple attention layers, the network is able to more efficiently capture the contextual correlations between neighboring samples in different modalities. Where the attention mechanism is shown in equation (7):

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{7}$$

where, Q represents the query matrix, K represents the key matrix, V represents the value matrix, and d_k represents the dimension of the key vector, which is used to scale the dot product for avoiding the overly large dot product value to make the softmax function enter into the region with very small gradient, which affects the model learning efficiency. In the self-attention mechanism, each element is mapped into these three vectors, and query attention is paid to the interior of the vectors, by which long-distance emotional dependencies within sequences or complex dependencies within image regions in emotion multimodality can be captured, which can help the model to better understand the details and contexts as well as the importance of the emotional vocabulary within the modality [36].

(3) Model structure

The structure of the multimodal sentiment analysis model based on graph attention neural network is shown in Figure 2. First, this paper introduces the process of self-attention mechanism to the graph attention neural network model, which is utilized to integrate the intra-modal dependencies independently within each modality. After that, these multimodal features processed by the self-attention mechanism are fed into the graph attention neural network. The graph attention neural network further models the global contextual information on these features and again models the global contextual information through the residual connectivity structure, as a result of which the multimodal affective features generated by the model present a richer and more comprehensive information content after being evaluated by the classifier. This approach ensures that the extraction of modal features can accurately map the actual sentiment states, enhances the model's ability to characterize the sentiment dimensions, and thus effectively optimizes the accuracy and processing speed of sentiment analysis.

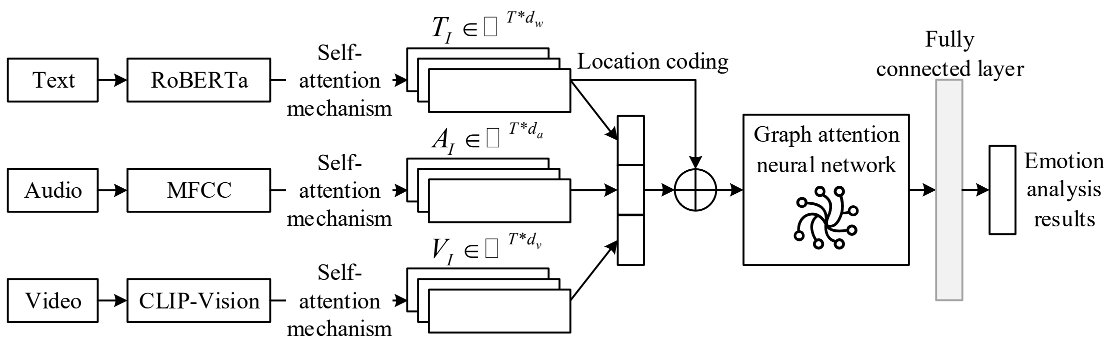


Figure 2: Multi-modal emotion analysis based on graph attention neural network

II. B.Knowledge Reasoning Module

The introduction of knowledge-based reasoning can improve the science and predictability of long-term care services. In this paper, we design a Knowledge Graph Temporal Reasoning based on Graph Representation Learning (KGTR_GRL) model for temporal information reasoning, so as to more accurately predict the physical condition of the elderly in the future moments, which is of great significance for the early initiation of cognitive intervention programs.

II. B. 1) Graph representation learning

In graph representation learning, supervised graph representation learning focuses on learning mapping relationships between inputs and outputs from labeled training samples, including vertex classification, edge prediction, and graph classification [37]. Comparatively, unsupervised learning focuses on learning graph structure or pattern information from unlabeled data, including graph embedding and community detection.

The knowledge graph temporal inference studied in this paper is an important area related to graph representation learning. Based on the temporal information to infer the change of the relationship between entities, by combining graph representation learning with knowledge graph temporal inference can better understand and predict the dynamic relationship between entities, and solve the problems of elderly people's physical condition prediction, time series analysis, and so on.

II. B. 2) Knowledge graph temporal reasoning

Existing inference methods for temporal knowledge graphs are mainly devoted to how to mine rules from temporal facts and synthesize statistical and temporal information for inference prediction. Although these methods consider temporal information, they are only simple extensions on static models, do not fully consider time series dependencies [38], and are often limited by the huge number of potential paths in the temporal knowledge graph.

To solve this problem, in this paper, we propose a prediction model based on temporal subgraphs, i.e., to predict facts $(s,r,?,t),(?,r,o,t)$ or $(s,?,o,t)$ at future t moments given a temporal subgraph $\{G_1,G_2,\dots G_t\}$, where "?" is the missing entity. The model is based on the existing set of facts in the temporal knowledge graph, and in order to capture the temporal information more deeply, the attention mechanism is introduced into the temporal encoder to predict the facts that may occur in the future moments, in order to select the fact with the highest probability as the prediction result.

II. B. 3) KGTR_GRL model

The KGTR_GRL model includes a multi-relational graph encoder, a timing encoder and a timing inference algorithm.

(1) Multi-relational graph structure encoder

The task of the structure encoder is to enable entities to fully perceive the information of the surrounding structure and obtain a richer semantic representation by updating the initialization of the entities. The structural encoder encodes the entities and relations in each temporal subgraph to obtain a static representation of the entities at each timestamp.

In each temporal subgraph G_t, the set of entities is represented as $E=\{e_1,e_2,\ldots,e_N\}$, where N is the number of entities. For the i th entity e_i, there are all temporal sense variables corresponding to it u_i. Entity e_i is represented as $e_{i,t}$ in the temporal subgraph (t moments), and its update variable is represented as $h_{i,t}$, then the set of update variables for all entities in the temporal subgraph is $H_t=\{h_{1,t},h_{2,t},\ldots,h_{N,t}\}$, with dimension d, which can be calculated by the following equation:

$$h_{i,t}=Wu_i \tag{8}$$

where W is the temporal subgraph weight.

In a particular time-series subgraph, $h_{i,t}$ contains limited feature information, so a structure encoder is needed to aggregate the neighborhood features of entities. In each time-series subgraph, the initialization aggregation update operation is performed on the entities by the structural encoder to output richer static entities $x_{i,t}$, then the set of all entities can be represented by $X_t=\{x_{1,t},x_{2,t},\ldots,x_{NJ}\}$.

In the field of knowledge graph, since traditional graph convolutional networks ignore the effect of relationships on node feature extraction, in this paper, Relational Graph Convolutional Neural (RGCN) network is proposed for optimizing the problem of multi-relationships in knowledge graph. The feature representation of entity nodes is obtained by aggregating the local neighborhood features of entity nodes and their own features in the relationship graph. The node update process in the multi-relationship graph encoder is shown in Fig. 3. As can be seen from the figure, each relationship and edge direction is considered in the N relationship types to update the node representation, which learns the relevant information of the neighboring points and makes the semantic representation of the entity richer.

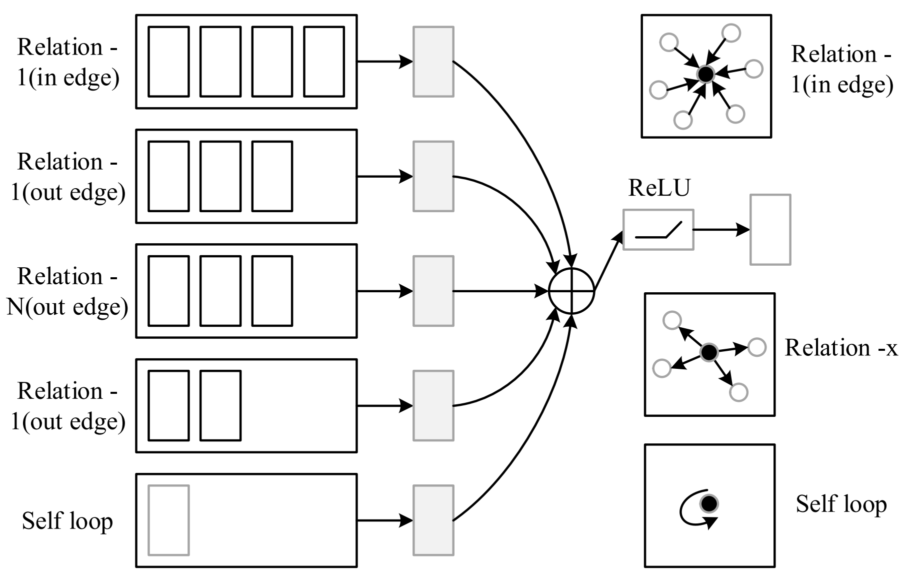


Figure 3: Node update process in multi-graph encoder

Since too many relationship layers may introduce many irrelevant neighbor node information, thus reducing the accuracy of entity embedding, the multi-relationship graph encoder designed in this paper uses a 2-layer RGCN, and the encoder structure is shown in Fig. 4.

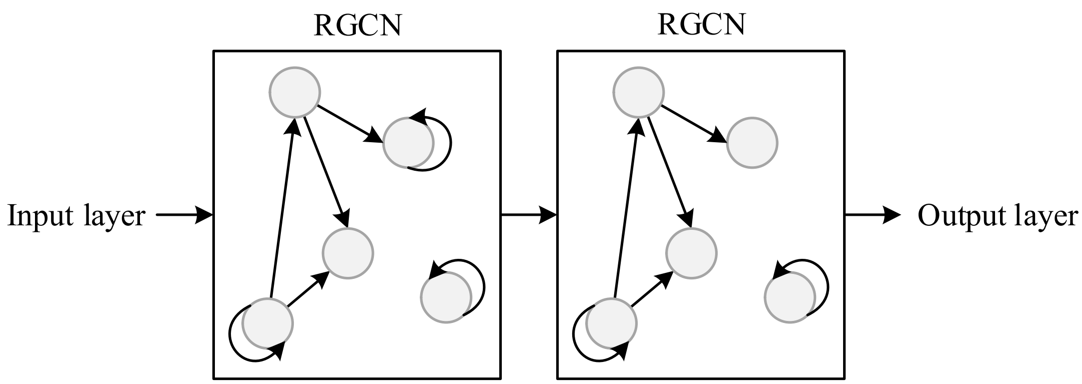


Figure 4: Schematic diagram of convolutional neural network (RGCN)encoder

The encoder inputs the initialization variables of entity nodes in the temporal subgraph G_t into a relational graph convolutional neural network to aggregate the features of neighboring nodes. After processing by the 2-layer relational graph convolutional neural network, the updated features of entity nodes X, are output. In this way, feature X_t is able to learn the feature information of the whole temporal subgraph G_t.

Each partial subgraph performs feature extraction and updating for the type and direction of edges. During the propagation process between network layers, the update variable $h_{i,t}$ is calculated as:

$$h_{i,t} = \sigma\left(\sum_{r \in R} W_r h_{j,t} + W_s h_{i,t}\right) \tag{9}$$

where, W_1 and W_2 are the 2 propagation weights of the network layer. $h_{j,t}$ is the update variable for the j th entity e_j.

(2) Time series encoder

There exists some potential connection between successive time-series subgraphs, where many of the facts are back-and-forth correlated and periodic. For example, at moment t_0 there exists <Elderly person, chest tightness and shortness of breath>, at moment t_1 there exists <Elderly person, low blood pressure>, and at moment t_2 there exists <Elderly person, fall>. With the fact of moment t_0, t_1, it can be observed that the old man first feels chest tightness and shortness of breath, and later finds out that his blood pressure is too low, then in the future moment t_2, it can be hypothesized that the old man may fall as a result. In order to better capture the temporal information, in this paper, a gated recurrent unit (GRU) based on the attention mechanism is used to learn the integrated information across time in the entity representation so as to form a dynamic representation of the set of entities in the temporal knowledge graph. The structure of the timing encoder is shown in Fig. 5.

The entity static variables $\{x_{i,t-\tau}, x_{i,t-\tau+1}, \ldots, x_{i,I}\}$ obtained through the structural encoder at moment t are input to the temporal encoder, and $x_i, i-\tau$ represent the static characteristics of the entity in the continuous temporal subgraph, where τ is the number of temporal subgraphs. The timing encoder employs GRUs to integrate the static representations of entity nodes in the continuous timing subgraph. In each gated loop unit, the GRU model updates and resets the long sequence information through a reset gate r_t and an update gate z_t. The reset gate determines how well the inputs at the current moment are combined with the previous memory, and the update gate determines how much of the previous sequence information is retained:

$$r_t = \sigma(W_r \cdot [s_{i,t-1}, x_{i,t}]) \tag{10}$$

$$z_t = \sigma(W_z \cdot [s_{i,t-1}, x_{i,t}]) \tag{11}$$

Where: W_r and W_z are the weights of reset gate r_t and update gate z_t, respectively. $s_{i,t-1}$ is the output of the hidden layer at moment $t-1$.

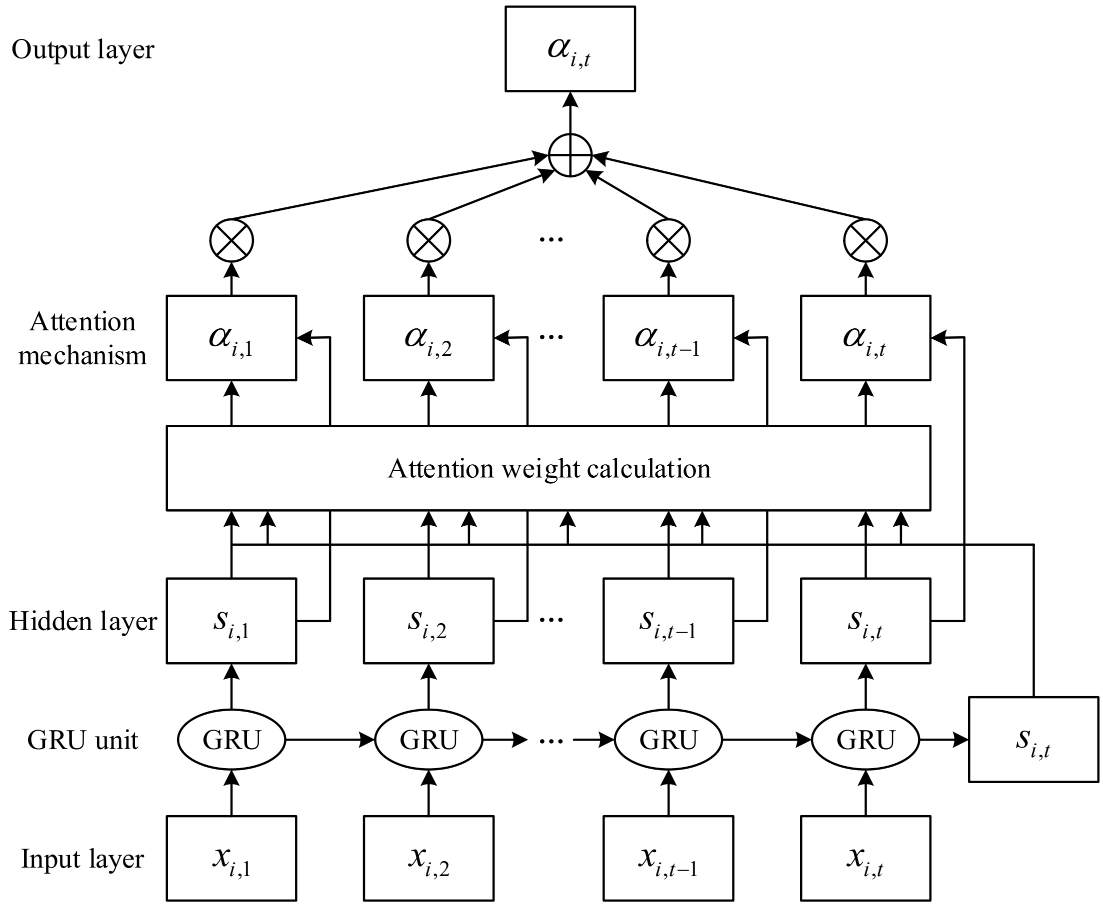


Figure 5: Structure of timing encoder

When the reset gate value is 1 and the update gate is 0, the model becomes a traditional recurrent neural network. The reset gate r_t resets the previous moment hidden state, and then the candidate hidden state is obtained by the tanh activation function as shown in equation (12). The update gate is used to perform forgetting and selecting operations on the current moment state and the memorized state to discard certain non-important information, as shown in equation (13) Hadamard product operation:

$$\tilde{s}_{i,t} = \tanh(s_{i,t-1} \cdot r_t, x_{i,t}) \tag{12}$$

$$s_{i,t} = (1 - z_t) \circ \vec{s}_{l,t} + z_t \circ s_{i,t-1} \tag{13}$$

After obtaining the hidden layer output $\{s_{i,t-\tau}, s_{i,t-\tau+1}, \ldots, s_{i,t-1}\}$ and GRU output $s_{i,t}$ of entity nodes at different moments, in order to calculate the importance of entity nodes before the current moment to the entity nodes at the t moment, the temporal encoder inputs $\{s_{i,t-\tau}, s_{i,t-\tau+1}, \ldots, s_{i,t-1}\}$ to the attention weight computation layer, and the attention weight $a_{i,j}$ of the node can be obtained by the projection of the corresponding operation, and the dynamic variables of the node are obtained by Eq. (14) $d_{i,t}$:

$$d_{i,t} = \alpha_{i,j} s_{i,t} \tag{14}$$

(3) Model Reasoning

In the time-series knowledge graph, only a small portion of entities are active in each time step, and the rest of the entities are in an inactive state. To address this situation, an update method for inactive entities is proposed in this paper to solve the problem that entity representations cannot be effectively updated. For each inactive entity node $e_{i,t}$, its static representation is obtained by combining the representation under the last active timestamp τ with the representation under the current timestamp t. The decay rate parameter θ is set in the KGTR_GRL model to simulate the law of diminishing marginal effect of the historical facts, and the decay rate decreases according to the time difference, which is calculated by the formula:

$$\theta = \exp\left\{-\max(0, \lambda_x \mid t - t^- \mid + b_x)\right\} \tag{15}$$

where λ_x and b_x are learning parameters. The updated $\hat{x}_i$ of an inactive entity is obtained by combining the variable x_{i,t^-} under its last active timestamp with the variable $x_{i,t}$ under the current timestamp. Finally, the original variable representations of the inactive entities are replaced with the updated variable representations to minimize the influence of the inactive entity nodes on the dynamic updates of other nodes. Through this optimization design, the embedding representations of the past neighboring moments are used to correct the current embedding representations, which ensures the accuracy of inactive entities' embedding, and also helps to alleviate the influence of inactive entities on the embedding of other entities, and improves the accuracy of the global knowledge reasoning.

III. Empirical analysis of integrated care models

The above section constructs a multimodal sentiment analysis model and a knowledge graph temporal inference model respectively based on the deep learning framework. This chapter analyzes the application performance of the two models respectively and empirically investigates the overall application effect.

III. A. Experimental analysis of the sentiment analysis model

III. A. 1) Indicators for model performance assessment

In this paper, regression indicators and classification indicators are used as performance evaluation criteria. The regression indicators include mean absolute error (MAE) and Pearson correlation coefficient (Corr), and the categorization indicators include Acc-7, Acc-5, Acc-2, and F1.

Specifically, Corr measures the degree of linear relationship between the predicted and true values and is calculated as follows:

$$Corr = \frac{cov(X,Y)}{\sigma_x \sigma_y} \tag{16}$$

where $cov(X,Y)$ denotes the covariance between Y and X, and σ_X and σ_Y are the standard deviations of Y and X, respectively.

MAE is used to quantify the mean absolute error between the predicted and true values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{17}$$

where n is the number of samples, y_i and $\hat{y}_i$ are the true and predicted values.

Accuracy is used to assess the classification accuracy. In order to comprehensively evaluate the performance of the model, this paper not only uses the binary (corresponding to the Binary formula in Eq. (18)) accuracy (Acc-2), but also introduces the multi-classification (corresponding to the Multi-class formula in Eq. (18)) accuracy indexes (Acc-5, Acc-7) as the evaluation criteria. The calculation formula is as follows:

$$Accuracy = \begin{cases} \dfrac{TP+TN}{TP+TN+FP+FN}, Binary \\ \dfrac{\sum_{i=0}^{n}\left[round(\hat{y}_i) = round(y_i)\right]}{n}, Multi-class \end{cases} \tag{18}$$

where $round(I)$ means $I \in \{\hat{y}_i, y_i\}$ rounded to the nearest integer. TP denotes true instances, TN denotes true negative instances, FP denotes false positive instances, and FN denotes false negative instances.

The F1-Score provides a combined measure of precision and recall in binary classification tasks:

$$F1-Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{19}$$

Among them:

$$Precision = \frac{TP}{TP + EP}$$
$$Recall = \frac{TP}{TP + FN} \tag{20}$$

III. A. 2) Data sets

The CMU-MOSI dataset collects 93 videos of monologues from video websites focusing on movie reviews from 89 different speakers, each of whom narrates their opinion about a particular movie or topic in the video. Each video ranged from 2 to 5 minutes in length, and the videos were divided into a total of 2,199 segments, each of which was manually labeled, with sentiment scores labeled as ranging from -3 to +3, where scores lower than zero indicate negativity and scores greater than zero indicate positivity.

III. A. 3) Contrasting models

In order to evaluate the performance of the methods proposed in this chapter, we compare multimodal sentiment analysis based on graph-attentive neural networks with state-of-the-art methods in multimodal sentiment analysis methods.

TFN: Inter-modal relationships are modeled using a tensor fusion approach that uses the triple Cartesian product to model unimodal, bimodal, and trimodal interactions.

LMF: Efficient multimodal fusion by decomposing the high-order weight tensor into modality-specific low-rank factors.

ICCN: Generating multimodal embedding features by learning the correlation between multimodalities through deep canonical correlation analysis.

MulT: proposes direction-paired cross-modal attention to focus on multimodal interactions at different time steps, adapting one modality to another.

MISA: Learning the commonalities between multimodalities and the properties of individual modalities by dividing two subspaces to better learn the modal representations to help fusion.

Self-MM: Sentiment analysis network obtains independent unimodal supervision by training unimodal tasks with a label generation module based on self-supervised learning.

MAG-BERT: is an improvement on RAVEN, which can be used in BERT models to utilize multimodal information for fine-tuning.

MMIM: maximizes mutual information in a hierarchical manner across modalities and between unimodal inputs and multimodal fusion results, better preserving modality critical information in the fusion results.

TEASEL: achieves better results without training the full Transformer by transforming speech information into token to be combined into a pre-trained language model.

EMT-DLFR: utilizes EMT and DLFR to achieve more efficient multimodal fusion and increase model robustness.

UniMSE: fully exploits the complementary relationship between emotion and sentiment to unify MSA and Emotion Recognition tasks.

III. A. 4) Experimental results and analysis

The performance comparison of the multimodal sentiment analysis model based on graph attention networks with the baseline model is shown in Figure 6. The model in this paper outperforms the existing state-of-the-art model (UniMSE) in most metrics. Specifically, it outperforms the best performing UniMSE by 0.39% Acc-2, 0.007 MAE, and 0.008 Corr. It sets a new record in Acc-5 and achieves the second best score in Acc-7. For the model not achieving satisfactory results in F1, this may be due to the imbalance of categories in the dataset.

Next, we performed a series of ablation experiments on CMU-MOSI, and the results are shown in Figure 7. The effect of modality on model performance was verified by deleting one or two modalities (w/o A for deletion of audio modality, w/o V for deletion of visual modality, w/o A,V for deletion of both visual and audio modalities). First, it can be observed that the multimodal combination provides the best performance, and deleting either of the visual and audio modalities reduces the model performance. This demonstrates the necessity of visual and audio modalities for multimodal sentiment analysis, and also shows that a multimodal sentiment analysis model based on graph attention networks is able to learn the interaction characteristics between modalities. In addition, the model's average performance is worst when both visual and audio modalities are removed, with a 2.03% decrease in accuracy and a 0.013 increase in average absolute error compared to the three modalities, suggesting that the three modalities are better than the two modalities, which in turn are better than a single modality, for the graph attention network-based multimodal sentiment analysis model, which is in line with the inference that multimodal data can provide more sentiment cues this inference.

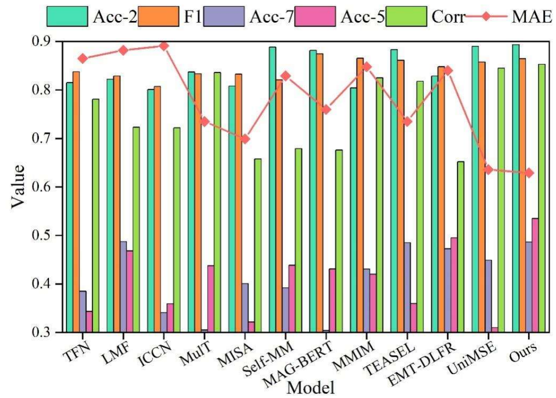


Figure 6: Experimental Results of this model on CMU-MOSI

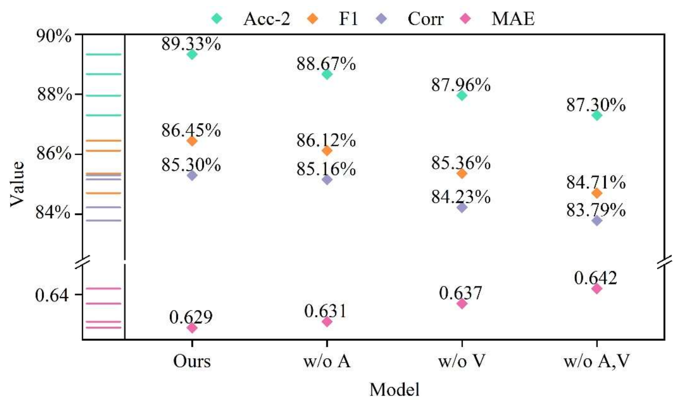


Figure 7: Ablation Study of this model

III. B. Experimental Analysis of Knowledge Reasoning Models

III. B. 1) Indicators for model performance assessment

Two classical assessment tasks, link prediction and ternary classification, are generally used to evaluate the effectiveness of model inference.

The evaluation metrics typically used for the link prediction task are:

(1) Mean ranking, the average of all ternary rankings of correctly predicted entities or relations.

(2) Top n Hits (Hits@n), the proportion of all correctly predicted entities or relationships whose ternary rankings are in the top n%, with n taking the usual values of 1, 3, and 10 in experiments:

$$MR = \frac{1}{M}\left(\sum_{i=1}^{M} rank_i\right) \tag{21}$$

$$Hit@n = \frac{right}{M \cdot n\%} \tag{22}$$

where M denotes the number of triples and RIGHT denotes the number of top k rankings in the predicted results. Lower MR values or higher Hits@n values indicate that the model performs better on the link prediction task, suggesting that the model's representation is more capable of learning and the knowledge is represented more accurately.

Ternary classification is the determination of the correctness of the given ternary and can be considered as a binary classification task. In the experiment as in link prediction it is necessary to construct negative example triples, and then for different relations, set a threshold σ for all of them, with different que values for different relations. Only ternaries with a score less than σ are recognized as correctly predicted: otherwise they are incorrect. Threshold σ is derived by maximizing the classification accuracy training the validation set.

The experiment uses accuracy as the evaluation metric for the classification results of this experiment, which is calculated by the formula:

$$\text{Accuracy} = \frac{|I_r|}{|I|} \tag{23}$$

where $|I_r|$ is the number of correctly categorized triples and $|I|$ is the number of all triples.

III. B. 2) Data sets

The dataset used in this chapter is an extension of the public dataset PatientEG. There are five types of events in the graph dataset, namely "Hospitalization-Event", "Diagnosis-Event", "Drug-Event", "Assay-Event", and "Surgery-Event", and the relationships between events are "before", "after", "during", "concurrent", and "overlap". After cleaning and sorting, PatientEG contains 13 types of knowledge entities, and this paper will add the knowledge entities and event subjects to the knowledge graph and assign an inclusion relationship. After preprocessing, there are 880163 triples in the PatientKG extended dataset, including 616534 triples between events and 263629 triples between events and knowledge entities. The triples in the dataset were divided into training set, test set and validation set according to the ratio of 6:2:2 by the random method.

III. B. 3) Contrasting models

In order to verify the effectiveness of the KGTR_GRL model, it was compared with the classical algorithms in the field of knowledge graph representation learning (including TransE, DKRL, TKRL, PTransE and EARP) in the experiment.

TransE: This model is the most representative translation model, which focuses on extracting semantic features contained in the triple structure of the knowledge graph and making predictions based on the structural information of the triple.

DKRL: This model is a representation learning model that incorporates entity descriptions, using a continuous bag-of-words model to extract entity-related semantic features contained in entity description texts, and using entity descriptions to enhance the expressive power of the knowledge graph.

TKRL: This model is a representation learning model that fuses entity types, classifies entity types into different levels through different relationships, and constructs mapping matrices to enhance the expressive power of the knowledge graph.

PTransE: This model is based on the TransE model, which considers multi-step paths, and obtains the representation of relational paths through a path resource constraint algorithm, embedded to express on triples. This model is applied to representation learning can improve the multi-step inference ability of knowledge graph.

EARP: Considers entity attribute information such as entity description and entity type as well as relational path information comprehensively in order to improve the event knowledge graph representation capability and reasoning performance.

III. B. 4) Experimental results and analysis

(1) Link prediction experiment results and analysis

The experimental results of link prediction are shown in Table 1. Comparing with the classical algorithmic models in the knowledge graph representation learning domain: the KGTR_GRL model can significantly outperform the TransE, DKRL, TKRL, PTransE and EARP models in the four evaluation indexes, especially in the Mean Rank and hits@10 indexes, the KGTR_GRL reaches 422 and 0.6533 respectively, the improvement effect is is relatively significant. This shows that the KGTR_GRL model has good link prediction performance, which can effectively improve the representation and inference of events.

Table 1: Link prediction results

Model	Mean Rank	Hits@n		
		n=1	n=3	n=10
TransE	1302	0.0982	0.1826	0.2597
DKRL	976	0.1095	0.1801	0.2672
TKRL	1092	0.0995	0.1764	0.2711
PTransE	869	0.1992	0.2346	0.2814
EARP	684	0.3085	0.3566	0.3922
KGTR_GRL	422	0.4373	0.5311	0.6533

(2) Experimental results and analysis of ternary group classification

The experimental results of ternary classification are shown in Fig. 8.The accuracy of KGTR_GRL model reaches 75.3%, which is higher than TransE, DKRL, TKRL, PTransE and EARP, which are the classical algorithmic models in the field of knowledge graph representation learning, which indicates that the KGTR_GRL model has an excellent performance in the classification task.

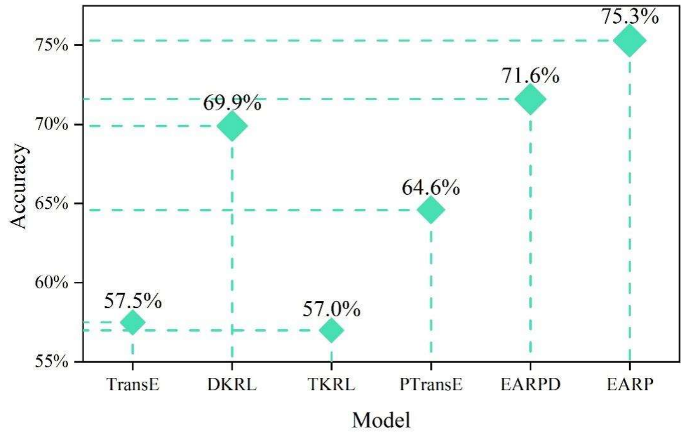


Figure 8: Results of the triples experiment

III. C. Evaluation of the Effectiveness of Integrated Nursing Model Application

Applying an integrated care model to an intelligent service robot system, a senior care facility in City D uses a service robot for long-term care for up to six months. After the integrated care model is applied to the service robot system, the sentiment analysis module can recognize the daily emotional changes of the elderly, chat with them and soothe their emotions. The knowledge reasoning module can help the elderly to predict their physical condition and popularize the knowledge of nursing safety in time. In order to explore the application effect of the integrated nursing model, this chapter carries out controlled experiments from the two aspects of the depression change situation of the elderly and the nursing safety knowledge mastery respectively.

III. C. 1) Research Objectives and Methodology

(1) General information

A convenience sampling method was used to select all 200 elderly people who met the inclusion criteria and stayed in an elderly care facility in City D from January to July 2024 as the study subjects.The general information of the 200 elderly people is shown in Table 2. The respondents contained 52 males and 148 females.

Table 2: General information for elderly people

Project		Number	Composition ratio/%
Gender	Male	52	26.0%
	Female	148	74.0%
Age	60~70	13	6.5%
	71~80	37	18.5%
	81~90	92	46.0%
	⩾91	58	29.0%
Cultural level	Unlearned	63	31.5%
	Primary school	99	49.5%
	Junior school	13	6.5%
	High school	25	12.5%
Long-term medication	Yes	133	66.5%
	No	67	33.5%
Chronic disease	Have	141	70.5%
	Nothing	59	29.5%
Fall down/time	⩾1	66	33.0%
	Nothing	134	67.0%

(2) Evaluation methods

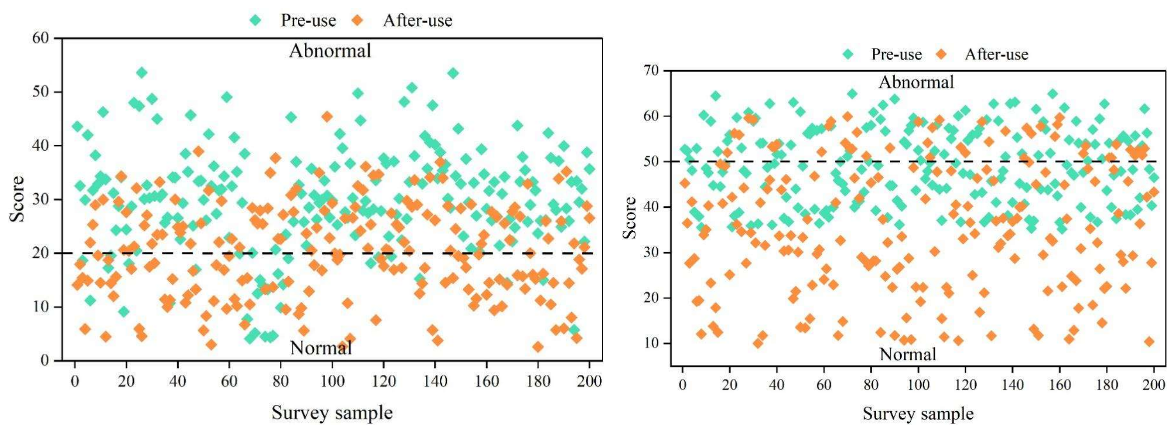
Changes in the level of depression of the elderly in nursing institutions were assessed using the Hamilton Depression Scale (HAMD) and the Self-assessment Depression Scale (SDS) scores, with HAMD scores of <20 and SDS scores of <50 regarded as normal.

Nursing care safety risk knowledge of the elderly in nursing institutions was assessed using a self-designed questionnaire on nursing care safety risk knowledge of the elderly in nursing institutions. The total score of the Nursing Safety Risk Knowledge Scale was the sum of the scores of five dimensions, including fall safety, medication safety, cognitive impairment risk, eating safety, and skin care safety.

Two studies were conducted on 200 older adults before and 6 months after the service robot was used to compare the effects before and after use.

III. C. 2) Analysis of changes in the level of depression

Comparison of HAMD and SDS scores before and after the use of the service robot in an elderly care facility is shown in Fig. 9, with (a) and (b) indicating the results of HAMD and SDS scores, respectively. From the figure, it can be visualized that after the use of the service robot, the number of people with HAMD and SDS scores below 20 and 50, respectively, increased, and the number of people with normal moods increased by 67 and 50, respectively, indicating that the service robot can effectively improve the depression condition of the elderly.



(a) HAMD (b) SDS

Figure 9: The service robot was compared with the HAMD and SDS scores

III. C. 3) Analysis of perceived mastery of nursing safety risks

In this subsection, Epidata software was applied to establish the database, and instant double entry comparison was performed to ensure the correctness and completeness of the data. SPSS 19.0 software was used to analyze the data, and the statistical description of count data was expressed as frequency and percentage, normally distributed measures were expressed as (x±s), and the comparison of means before and after itself was performed using t-test for paired data. Spearman correlation analysis was used to analyze the general demographic variables of the elderly with the risk of nursing safety. Differences were considered statistically significant at $P<0.05$.

The results of Spearman's correlation analysis between the general demographic variables of older adults and the dimensions and total scores of nursing safety risk before and after the use of the service robot are shown in Tables 3 and 4. "*" indicates that the correlation is significant at a confidence level (two-test) of 0.01. Only the cognitive impairment risk dimension was significantly different ($P<0.05$) on the variables of gender and long-term medication before service robot use. The literacy level variable showed significant differences overall after use.

The comparative analysis of the nursing care safety risk perception scores of the elderly before and after the use of the service robot is shown in Table 5. After the service robot was used for 6 months, the scores of all dimensions and the total scores of the elderly in the nursing institutions were significantly higher than those before the use of the service robot ($P<0.001$), indicating that the application of the integrated care model to the intelligent service robot system can significantly improve the level of nursing care safety risk perception of the elderly after the long-term use of the service robot.

Table 3: Spearman related analysis results of service robots

		Gender	Age	Cultural level	Long-term medication	Chronic disease	Fall down/time
Fall safety	R	-0.006	0.11	0.015	0.018	0.107	0.128
	P	0.87	0.144	0.997	0.78	0.135	0.076
Drug safety	R	0.021	0.088	-0.04	-0.048	-0.025	0.019
	P	0.737	0.214	0.62	0.566	0.723	0.759
Risk of cognitive impairment	R	-0.202	-0.035	0.019	-0.032	-0.006	0.038
	P	0.002*	0.639	0.74	0.656	0.911	0.007
Eating safety	R	-0.006	0.061	-0.045	-0.13	-0.068	-0.003
	P	0.99	0.327	0.538	0.065	0.402	0.98
Skin care safety	R	-0.001	0.007	-0.003	-0.1	-0.136	-0.126
	P	0.937	0.842	0.936	0.173	0.054	0.092
Total score	R	-0.054	0.071	-0.012	-0.096	-0.025	0.048
	P	0.003*	0.324	0.865	0.262	0.71	0.601

Table 4: Spearman related analysis results after service robot

		Gender	Age	Cultural level	Long-term medication	Chronic disease	Fall down/time
Fall safety	R	-0.13	-0.038	0.142	-0.036	-0.102	-0.091
	P	0.074	0.585	0.047*	0.627	0.187	0.206
Drug safety	R	-0.087	-0.001	0.165	-0.035	-0.128	-0.108
	P	0.29	0.983	0.022*	0.646	0.085	0.15
Risk of cognitive impairment	R	-0.112	-0.027	0.139	-0.017	-0.064	-0.044
	P	0.096	0.798	0.047*	0.828	0.398	0.534
Eating safety	R	-0.088	0.004	0.121	-0.139	-0.118	-0.118
	P	0.232	0.994	0.09	0.072	0.133	0.119
Skin care safety	R	-0.095	-0.031	-0.054	-0.117	-0.132	-0.051
	P	0.167	0.753	0.445	0.117	0.079	0.479
Total score	R	-0.118	-0.016	0.149	-0.073	-0.116	-0.086
	P	0.095	0.753	0.039*	0.325	0.148	0.213

Table 5: Comparison of nursing safety risk cognitive score

	Fall safety	Drug safety	Risk of cognitive impairment	Eating safety	Skin care safety	Total score
Pre-use	25.77±5.57	23.34±5.22	19.18±4.01	24.66±4.41	17.38±3.63	110.33±14.93
After-use	37.63±4.05	33.93±3.22	24.16±3.52	26.83±3.24	24.07±3.33	146.62±15.32
T	-22.965	-18.933	-13.541	-12.159	-14.963	-22.556
P	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

In summary, applying the integrated care model to the intelligent service robot system, the service robot can accurately give psychological comfort to the elderly after their depressed mood is recognized by the multimodal sentiment analysis model. And the KGTR_GRL model can effectively predict the related risks that the elderly may encounter and popularize the knowledge of nursing safety in time.

IV. Conclusion

For long-term care of the elderly, this paper designs an integrated care model combining sentiment analysis and knowledge reasoning based on a deep learning framework. After testing the performance of each module, the following conclusions are drawn through empirical analysis to verify the performance of each module and the overall use effect:

(1) The multimodal sentiment analysis model based on graph attention networks outperforms the baseline model in most metrics, exceeding the Acc-2 and Corr values by 0.39% and 0.008, respectively, and decreasing the MAE by 0.007 compared to the best-performing UniMSE model, and the model outperforms the unimodal model when performing multimodal sentiment analysis.

(2) Evaluate the performance of KGTR_GRL model on Mean Rank and hits@10 metrics. KGTR_GRL model has good link prediction performance with Mean Rank and hits@10 of 422 and 0.6533, respectively. In the ternary classification experiments, the accuracy of KGTR_GRL model reaches 75.3%, and the prediction of inference models accuracy is more satisfactory.

(3) After the integrated care model was applied to the service robot system, the number of elderly people with normal emotions increased significantly. The total nursing safety risk perception score improved by 36.29 points, showing a significant difference ($P<0.001$).

The comprehensive nursing model designed in this paper can effectively improve the mood of the elderly and enhance the nursing safety risk perception after long-term use.

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