Improving the Accuracy of Multi-Dimensional Cost Allocation in Public Hospitals Using a GNN-RL Hybrid Strategy Discrete Optimization Algorithm

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ABSTRACT Cost allocation in public hospitals represents a core link in the optimal allocation of medical resources and the enhancement of operational efficiency. This systematic approach ensures that financial resource is reasonably allocated to form a sustainable framework that supports both clinical excellence and organizational stability. Traditional allocation methods have problems such as a single dimension, reliance on subjective assumptions, and poor dynamic adaptability, leading to insufficient allocation accuracy. This paper proposes a hybrid strategy discrete optimization algorithm based on Graph Neural Networks (GNN) and Reinforcement Learning (RL). It mines the complex correlation features between cost elements through GNN and uses RL to realize the learning of optimal allocation strategies in dynamic environments. Taking the operational data of 3 tertiary public hospitals from 2019 to 2023 as samples, a multidimensional cost allocation index system (including categories and 12 indicators: direct costs, indirect costs, and implicit costs) was constructed, and comparative experi ments were carried out. The results show that the allocation error rate of the proposed algorithm is 18.7% lower than that of the traditional Activity-Based Costing (ABC) and 11.3% lower than that of the Genetic Algorithm (GA). It performs better in scenarios such as cross-departmental cost allocation and adaptation to dynamic cost fluctuations. This study provides new technical support for the accurate cost accounting of public hospitals and the reform of medical insurance payment methods.

INDEX TERMS public hospitals,cost allocation,graph neural network,reinforcement learning,medical equipment management

I. INTRODUCTION

A. RESEARCH BACKGROUND

As we all know, public hospitals are the main force of China's medical and health service system and the key object of the medical and health system reform [1]. With the gradual advancement of medical price reform, medical insurance payment reform, medical cost control, and hierarchical diagnosis and treatment payment required by national policies, the growth rate of public hospitals' income has been decreasing year by year, while the cost has been continuously increasing [2, 3]. Under the tide of medical reform, the current management of public hospitals has increased their own operational pressure. In order to respond to the national call and solve the existing revenue and expenditure challenges, public hospitals must transform to refined management, which makes them realize that cost management has become an important development direction [4, 5]. Cost control has gradually highlighted its importance in modern hospital management, reflecting the same rigorous precision required in cost engineering where every thread of expenditure must be meticulously managed to ensure the realization of sustainable operational excellence. This shift toward systematic cost management mirror the structural integrity of high-quality fabrics, where the careful balance of material inputs and process efficiency determines the overall strength and viability of the organization [6].

In 2021, the National Health Commission issued the "Notice on the Specifications for Cost Accounting of Public Hospitals", which put forward various provisions for the operation and management of public hospitals, such as actively participating in market competition and forming a standardized and refined cost accounting system [7]. This series of people-benefiting policies is a difficult challenge for the current operation of public hospitals. How to continuously strengthen their own competitiveness, achieve "opening up sources of revenue and cutting down on expenses", and realize the balance of revenue and expenditure under the premise of reflecting their own "public welfare" has become an important issue at present.

To meet internal and external challenges, public hospitals should actively make changes and develop towards refined cost management. However, according to the current research situation, the refined cost management of most public hospitals in China still faces many challenges. Problems such as single cost accounting and inefficient control seriously hinder hospitals from improving their economic benefits [8, 9]. The birth and development of information technology have made intelligent cost management possible and injected new content into the concepts and methods of cost management [10]. In recent years, machine learning algorithms have begun to be used for cost management optimization [11]. This paper intends to adopt the GNN-RL hybrid strategy discrete optimization algorithm to improve the accuracy of multi-dimensional cost allocation in public hospitals, drawing inspiration from the complex pattern-matching and resource-balancing techniques found in high-precision manufacturing to provide a theoretical basis and practical guidance for the reform of medical cost accounting. By simulating the intricate structural optimization of woven fabrics, this hybrid approach aims to weave diverse financial data points into a cohesive and efficient resource management framework.

B. RESEARCH STATUS

Hospital cost management needs to proceed from various aspects and angles through multiple paths such as hospital cost budgeting, cost accounting, cost analysis, and cost control.

In the mid-20th century, the idea of cost accounting first appeared in Western European countries. At that time, the cost accounting method implemented by various hospitals in the United States actually determined the cost according to the department category. Such accounting had great limitations and lacked a scientific and reasonable accounting system [12]. There are not many relevant studies on the development and implementation of cost accounting by hospital management experts and scholars in China. Hu Shanlian (1992) proposed that hospitals should carry out different levels of cost accounting according to different management objects, and on this basis, carry out a series of cost management activities such as cost analysis, cost control, and cost assessment to provide decision-making information for hospital managers, scientifically analyze the development status of hospitals, and strive to obtain the optimal benefits with the least investment [13]. Yang Jihong (2007) believed that public hospitals have gradually found that full cost accounting is a new hope for their sustainable development, which can provide a reliable basis for management decisions, become an effective lever for management control, and provide accurate data for financial accounting [14].

Some scholars have conducted relevant research on the countermeasures of full cost accounting. Helmi & Tanju (1991) proposed that the selection of reasonable cost drivers is crucial for Activity-Based Costing (ABC). Generally, a working group composed of cost accountants, cost control experts, production engineers and other personnel should regard the enterprise as a value chain combination, fully consider the comprehensiveness of driver selection, so as to closely cooperate with other departments [15]. Yu Weijia (2013) proposed that hospital full cost accounting should pay attention to accounting pre-control, and do a good job in comprehensive cost budgeting before the occurrence of daily economic activities, which is helpful for cost control and management. A small number of public hospitals in China have implemented full cost accounting, but there are still some problems in the details of the accounting process [16].

At present, the relatively mature cost accounting method is Activity-Based Costing [17-19]. With the proposal of Activity-Based Costing, the traditional cost accounting method has been greatly improved, but it has limita tions such as simple allocation coefficient and strong subjectivity in calculation when applied in the actual cost management of enterprises [20]. Therefore, on the basis of Activity-Based Costing, in order to alleviate the adverse effects of these limitations, some scholars have upgraded the traditional Activity-Based Costing in their research. Considering both activity cost and time management, they proposed a more standardized Time-Driven Activity-Based Costing. This method estimates the allocation coefficient by combining the time calculation model and the productivity cost ratio, alleviates the limitation of strong subjectivity, and has been rapidly promoted in enterprises. Domestic research mainly focuses on the application optimization of Activity-Based Costing in public hospitals, improving the accuracy of departmental cost allocation by refining the operation process, but fails to solve the problem of model adaptability in dynamic environments.

C. RESEARCH OBJECTIVES AND INNOVATIONS

1) Research Objectives

Aiming at the limitations of traditional methods, this paper constructs a GNN-RL hybrid strategy discrete optimization algorithm to realize the accurate allocation of multi-dimensional costs in public hospitals. The specific objectives include:

(1) Establish a multi-dimensional allocation index system covering direct, indirect, and implicit costs;

(2) Mine the complex correlations between cost elements and allocation objects through GNN;

(3) Use RL to learn the optimal allocation strategy in dynamic environments;

(4) Verify the allocation accuracy and adaptability of the algorithm through empirical studies.

2) Innovations

(1) Propose a multi-dimensional cost allocation framework, and incorporate implicit costs (such as medical dispute risk costs and implicit costs of scientific research investment) into the allocation system for the first time;

(2) Construct a GNN-RL hybrid model, integrating the feature extraction ability of GNN and the decision optimization ability of RL to solve the combinatorial optimization problem of discrete cost allocation; (3) Design a dynamic reward mechanism based on environmental feedback to improve the algorithm's adaptability to dynamic scenarios such as fluctuations in medical service volume and policy adjustments.

II. CONSTRUCTION OF MULTI-DIMENSIONAL COST ALLOCATION INDEX SYSTEM FOR PUBLIC HOSPITALS

A. PRINCIPLES FOR INDEX SYSTEM DESIGN

Follow the principles of comprehensiveness, relevance, operability, and objectivity to ensure that the indica tors can not only cover the main cost types of public hospitals, but also accurately reflect the correlation between cost consumption and allocation objects, while taking into account data availability and calculation feasibility.

B. CLASSIFICATION OF MULTI-DIMENSIONAL COST INDICATORS

1) Direct Cost Dimension (C1)

Direct costs refer to costs directly related to medical services and directly traceable to departments or service items, including:

- C11: Direct personnel remuneration (salaries and bonuses of front-line personnel such as doctors and nurses);
- C12: Drug and consumable costs (costs of drugs and medical consumables directly used in patient treatment);
- C13: Direct equipment depreciation (depreciation costs of special medical equipment in departments);
- C14: Direct medical expenses (direct water, electricity, and site occupancy fees for departments to carry out diagnosis and treatment activities).

2) Indirect Cost Dimension (C2)

Indirect costs refer to public costs that need to be allocated among multiple departments to ensure the normal development of medical services, including:

- C21: Management expenses (expenses of hospital administrative, financial, logistics and other manage ment departments);
- C22: Public equipment depreciation (depreciation of large-scale shared equipment such as CT and MRI);
- C23: Public service costs (service costs of public departments such as disinfection supply centers and inspection centers);
- C24: Training and education costs (training and continuing education expenses for medical staff in the hospital).

3) Implicit Cost Dimension (C3)

Implicit costs refer to costs that are not directly included in financial statements but have a substantial impact on hospital operations, including:

- C31: Medical dispute risk costs (expected losses calculated based on historical dispute data);
- C32: Implicit costs of scientific research investment (investment in scientific research equipment and human resources that have not formed direct outputs);
- C33: Patient waiting costs (the potential lost revenue of the hospital caused by patient loss due to excessive waiting time, calculated as $C_{\text{wait}} = \sum_{i=1}^{n} (T_i - T_0) \times P_i \times Q_i$, where T_i is the actual waiting time of the i-th patient group, T_0 is the waiting time threshold, P_i is the patient loss rate corresponding to the excess waiting time, and Q_i is the average medical consumption per patient of the i-th group);
- C34: Environmental depletion costs (implicit costs for medical waste disposal and energy consumption pollution control).

C. DETERMINATION OF INDEX WEIGHTS

The Entropy Weight-Analytic Hierarchy Process (EW-AHP) is used to determine the index weights, considering both objective data characteristics and expert experience:

1) Construct a hierarchical structure: target layer (multi-dimensional cost allocation), criterion layer (3 types of costs), and index layer (12 specific indicators);

2) Calculate objective weights using the entropy weight method: based on 5-year data from 3 hospitals, calculate the information entropy and weight of each indicator;

3) Calculate subjective weights using the AHP method: invite 10 hospital financial and operation management experts to construct a judgment matrix and conduct consistency check (CR $<$ 0.1) to ensure the rationality of the judgment matrix;

4) Combined weights: use the weighted average method to integrate subjective and objective weights, and the final weight results are shown in Table 1.

TABLE 1. Multi-Dimensional Cost Allocation Indicators and Weights

Criterion Layer	Index	Indicator Meaning	Objective Weight	Subjective Weight	Combined Weight
Direct Costs (C1)	C11	Direct personnel remuneration	0.128	0.135	0.132
Direct Costs (C1)	C12	Drug and consumable costs	0.156	0.162	0.159
Direct Costs (C1)	C13	Direct equipment depreciation	0.098	0.102	0.100
Direct Costs (C1)	C14	Direct medical expenses	0.085	0.078	0.082
Indirect Costs (C2)	C21	Management expenses	0.076	0.085	0.081
Indirect Costs (C2)	C22	Public equipment depreciation	0.112	0.108	0.110
Indirect Costs (C2)	C23	Public service costs	0.095	0.092	0.093
Indirect Costs (C2)	C24	Training and education costs	0.042	0.038	0.040
Implicit Costs (C3)	C31	Medical dispute risk costs	0.068	0.072	0.070
Implicit Costs (C3)	C32	Implicit costs of scientific research investment	0.052	0.056	0.054
Implicit Costs (C3)	C33	Patient waiting costs	0.061	0.058	0.060
Implicit Costs (C3)	C34	Environmental depletion costs	0.027	0.028	0.027
Total	–	–	1.000	1.000	1.000

III. DESIGN OF GNN-RL HYBRID STRATEGY DISCRETE OPTIMIZATION ALGORITHM

A. OVERALL ALGORITHM FRAMEWORK

The GNN-RL hybrid algorithm is divided into a feature extraction layer (GNN) and a decision optimization layer (RL):

- The feature extraction layer mines the correlation features between cost elements and allocation objects (departments, service items) through GNN;
- The decision optimization layer takes the feature vector output by GNN as the state input, and learns the optimal combination of allocation coefficients through RL to achieve the discrete optimization goal.

The cost allocation system is modeled as a heterogeneous graph (G= (V, E, A)) , where:

- Node set (V= VC∪VO) : (VC) is the cost node (12 cost indicators), and (VO) is the allocation object node (20 clinical departments such as internal medicine, surgery, and obstetrics and gynecology);
- Edge set E: represents the correlation between cost nodes and allocation object nodes. eij∈Erepresents the correlation strength between the i-th cost indicator and the j-th allocation object (correlation coefficient calculated based on historical data);
- Adjacency matrix A: dimension is (| VC| + | VO|) × (| VC| + | VO|) , Aij= eij, and Aij= 0 when there is no correlation.

B. GNN MODEL SELECTION AND TRAINING

Graph Attention Network (GAT) is used to extract node features, and the edge weights are adaptively assigned through the attention mechanism to capture the nonlinear correlations between costs and allocation objects:

1) Node feature initialization:

- Cost node feature vector $X_C \in \mathbb{R}^{12\times d}$ ($d = 64$ is the feature dimension), including indicator values, weights, fluctuation coefficients, etc.;
- Allocation object node feature vector $X_O \in \mathbb{R}^{20\times d}$, including service volume, personnel scale, equipment quantity, etc.;

2) Attention mechanism calculation: For each node v_i, calculate the attention coefficient α_{ij} with its neighbor node v_j:

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(a^T[WX_i \| WX_j]\right)\right)}{\sum_{k\in N(i)}\exp\left(\text{LeakyReLU}\left(a^T[WX_i \| WX_k]\right)\right)} \tag{1}$$

Where, $W \in \mathbb{R}^{d'\times d}$ is the weight matrix, $a \in \mathbb{R}^{2d'}$ is the attention vector, and $N(i)$ is the neighbor set of node i;

- Feature aggregation: Aggregate neighbor features through the multi-head attention mechanism to obtain the final node feature vector $H \in \mathbb{R}^{(12+20)\times d'}$;
- Training objective: Take the minimization of cost allocation error as the loss function to optimize the model parameters W and a.

C. DECISION OPTIMIZATION LAYER: REINFORCEMENT LEARNING (RL) DESIGN

1) Definition of RL Core Elements

1) State space S: The feature vector of the allocation object node output by GAT is taken as the state. $s_t = H_O(t) \in \mathbb{R}^{20\times d'}$, where $H_O(t)$ is the feature vector of 20 departments at time t;

2) Action space A: Discrete action space. The action $a_t = (x_{1t}, x_{2t}, \ldots, x_{20t})$ represents the cost allocation coefficient of each department, satisfying $\sum_{j=1}^{20} x_{jt} = 1$, $x_{jt} \in [0, 1]$ and being a discrete value (step size 0.01);

3) Reward function R: Design a multi-objective reward function considering both allocation accuracy and fairness:

$$R(t) = \lambda_1 R_{acc}(t) + \lambda_2 R_{fair}(t) - \lambda_3 R_{cost}(t) \tag{2}$$

Where:

- $R_{acc}(t) = 1 - \frac{\left|\hat{C}_j(t) - C_j(t)\right|}{\sum_{j=1}^{20} C_j(t)}$ (allocation accuracy rate, $\hat{C}_j(t)$ is the predicted allocated cost, $C_j(t)$ is the actual cost);
- $R_{fair}(t) = 1 - CV(\hat{C}_j(t))$ (allocation fairness, CV is the coefficient of variation);
- $R_{cost}(t)$ is the algorithm calculation cost (normalized);
- $\lambda_1 = 0.6$, $\lambda_2 = 0.3$, $\lambda_3 = 0.1$ are weight coefficients, determined through sensitivity analysis of 9 groups of weight combinations.

4) Policy network: Deep Q-Network (DQN) is used as the policy network. Input the state s_t, output the Q value

of each action, and select the action with the maximum Q value as the optimal allocation strategy.

2) Algorithm Training Process Initialization

1) Randomly initialize: GAT model parameters and DQN network parameters, and set the capacity of the Prioritized Experience Replay (PER) buffer to 10000;

2) Data preprocessing: Divide the 5-year data of 3 hospitals into training set and test set at a ratio of 7:3, and construct the graph structure after standardization;

3) GAT training: Train the GAT model based on the training set data until the loss function converges (loss value ≤ 0.001);

4) RL interactive training:

- For each training cycle t, obtain the state s_t (allocation object features output by GAT);
- Select the action a_t based on the ϵ-greedy strategy (ϵ linearly decays from 0.9 to 0.1);
- Calculate the actual allocated cost $C(t)$ and obtain the reward $R(t)$;
- Store $(s_t, a_t, R(t), s_{t+1})$ in the experience replay buffer;
- Randomly sample experience samples, update DQN network parameters with dynamic learning rate (initial learning rate 0.001, decaying by 10% every 1000 episodes), and minimize the temporal difference error;

5) Termination condition: The training ends when the reward function R(t) is stably above 0.8 for 100 consecutive cycles.

D. DISCRETE OPTIMIZATION IMPLEMENTATION

The discreteness of cost allocation coefficients requires the action space to be a finite set. This paper realizes discrete optimization in the following ways:

1) Action space discretization: Divide the allocation coefficient of each department into 101 discrete values (0, 0.01, 0.02, ..., 1.0), satisfying $\sum x_{jt} = 1$;

2) Constraint handling: Add a penalty term to the reward function. If the sum of allocation coefficients deviates from 1, a negative reward is given;

3) Avoidance of local optimal solutions: Guide RL exploration through the global correlation features extracted by GAT, and ensure action diversity combined with the ϵ-greedystrategy.

IV. EMPIRICAL EXPERIMENTS AND RESULT ANALYSIS

A. EXPERIMENTAL DATA

Select the operational data of 3 tertiary general hospitals (Hospital A, Hospital B, Hospital C) from 2019 to 2023, including financial statements, departmental service volume, equipment accounts, personnel informa tion, etc. The data sources are the hospital's HIS system, financial system, and statistical yearbooks. Each hospital includes 20 clinical departments, 5 medical technology departments, and 8 administrative and logistics departments. A total of 1500 valid samples are extracted (100 samples per hospital per year). Data preprocessing includes missing value imputation (using KNN algorithm), outlier elimination (STL decom position method to process pandemic-related outliers: separate the data into trend component, seasonal component, and residual component; retain the trend component, and adjust the residual component using the 3σprinciple to eliminate the abnormal impact of the 2020–2021 pandemic period), and standardization.

B. SELECTION OF COMPARATIVE ALGORITHMS

Select 4 mainstream cost allocation methods for comparison:

1) Traditional methods: Activity-Based Costing (ABC), Revenue Proportion Method (RPM);

2) Intelligent algorithms: Genetic Algorithm (GA), Single DQN Algorithm (only RL without GNN).

C. EVALUATION INDICATORS

Three core indicators are used to evaluate allocation accuracy and algorithm performance:

1) Mean Absolute Error Rate (MAER):

$$MAER = \frac{1}{N}\sum_{j=1}^{N}\frac{\left|\hat{C}_j - C_j\right|}{C_j}$$

where C_j is the benchmark cost calculated by the weighted average of ABC, RPM, and expert evaluation(weight ratio 4:3:3), reflecting the degree of allocation error, the smaller the better;

2) Coefficient of Variation (CV): $\left(CV = \frac{\mathrm{std}(\hat{C}_j)}{\left|\bar{\hat{C}}_j\right|}\right)$, reflecting allocation fairness, the smaller the fairer;

3) Calculation Time (CT): The average time (seconds) for the algorithm to complete one allocation, reflecting real-time performance.

D. EXPERIMENTAL RESULTS AND ANALYSIS

1) Comparison of Allocation Accuracy

Table 2 shows the MAER and CV indicator results of different algorithms on the test set. It can be seen that:

- The GNN-RL algorithm proposed in this paper has the lowest MAER (3.27%), which is 18.7% lower than ABC (4.02%), 11.3% lower than GA (3.69%), and 14.9% lower than single DQN (3.85%), indicating that the mining of correlation features by GNN effectively improves the allocation accuracy;
- The CV value of GNN-RL (0.18) is lower than that of other algorithms, indicating that it takes into account the allocation fairness among departments while ensuring accuracy;
- The traditional RPM method has the lowest accuracy (MAER=6.85%), verifying the limitations of traditional methods in multi-dimensional cost allocation.

To further verify the rationality of the benchmark cost, we compared the MAER of the algorithm with the benchmark cost and the individual traditional method costs. The results show that the MAER relative to the benchmark cost (3.27%) is lower than the MAER relative to the individual ABC cost (3.89%) and RPM cost (4.52%), indicating that the benchmark cost can more objectively reflect the actual cost level of the hospital, and the algorithm's accuracy advantage is more reliable.

TABLE 2. Comparison of Allocation Accuracy and Fairness of Different Algorithms

Algorithm	MAER	CV
Revenue Proportion Method (RPM)	6.85%	0.32
Activity-Based Costing (ABC)	4.02%	0.25
Genetic Algorithm (GA)	3.69%	0.21
Single DQN Algorithm	3.85%	0.23
GNN-RL Hybrid Algorithm	3.27%	0.18

2) Dynamic Adaptability Test

To verify the performance of the algorithm in dynamic environments, scenarios such as fluctuations in medical service volume (±20%) and an increase in management expenses (15%) are simulated, and the MAER change rate is tested. The results are shown in Table 3.

The MAER change rate of the GNN-RL algorithm in each dynamic scenario is less than 5%, which is significantly better than other algorithms, indicating that it has strong environmental adaptability through the dynamic learning mechanism of RL.

Additionally, we added a comparative analysis of the model performance before and after pandemic outlier processing: in the service volume fluctuation scenario, the MAER change rate of the unprocessed data model is 7.8%, while the MAER change rate of the processed data model is 4.1%, verifying that the STL decomposition method effectively eliminates the abnormal impact of the pandemic and improves the model's dynamic adaptability.

TABLE 3. Comparison of Algorithm Adaptability in Dynamic Scenarios (MAER Change Rate)

Dynamic Scenario	RPM	ABC	GA	Single DQN	GNN-RL (Unprocessed)	GNN-RL (Processed)
Service Volume +20%	12.3%	8.7%	6.2%	7.5%	7.8%	4.1%
Service Volume -20%	10.8%	7.9%	5.8%	6.9%	7.2%	3.8%
Management Expenses +15%	15.6%	10.2%	7.3%	8.8%	8.5%	4.7%
Implicit Cost Fluctuation	18.2%	12.5%	8.5%	9.6%	9.3%	4.9%

3) Comparison of Computational Efficiency

Table 4 shows the comparison of calculation time of each algorithm. The average calculation time of the GNN- RL algorithm is 0.87 seconds, which is slightly longer than that of RPM and ABC, but much lower than that of GA (2.35 seconds), meeting the real-time requirements of daily cost allocation in public hospitals. This is due to the efficient feature extraction of GAT and the batch update mechanism of DQN, which balances accuracy and efficiency. The sensitivity analysis of the reward function weights also shows that the calculation time of the algorithm is stable within 0.78–0.91 seconds under different weight combinations, indicating that the model has good computational stability.

TABLE 4. Comparison of Computational Efficiency of Different Algorithms

Algorithm	Average Calculation Time (seconds)
Revenue Proportion Method (RPM)	0.21
Activity-Based Costing (ABC)	0.35
Genetic Algorithm (GA)	2.35
Single DQN Algorithm	1.02
GNN-RL Hybrid Algorithm	0.87

4) Analysis of Allocation Accuracy in Each Cost Dimension

Further analyze the allocation accuracy of the algorithm in different cost dimensions, and the results are shown in Table 5.

The MAER of the GNN-RL algorithm in the indirect cost and implicit cost dimensions are 3.52% and 4.18% respectively, which are significantly better than other algorithms, indicating that it effectively solves the problem of difficult allocation of indirect costs and implicit costs by mining complex correlation features through GNN.

The accuracy of each algorithm in the direct cost dimension is slightly different, indicating that traditional methods still have a certain effect in direct cost tracing, but the GNN-RL has obvious advantages in multidimensional comprehensive scenarios.

TABLE 5. Comparison of MAER of Cost Allocation in Each Dimension (%)

Cost Dimension	RPM	ABC	GA	Single DQN	GNN-RL
Direct Costs	3.12	2.05	1.87	1.79	1.63
Indirect Costs	8.76	5.32	4.68	4.35	3.52
Implicit Costs	12.58	7.89	6.92	6.43	4.18
Comprehensive Costs	6.85	4.02	3.69	3.85	3.27

V. DISCUSSION

A. ALGORITHM ADVANTAGES AND APPLICATION VALUE

1) Technical Advantages

(1) Multi-dimensional feature fusion: Capture the complex correlations between cost elements and allocation objects through GNN, breaking the limitation of the "linear assumption" of traditional methods;

(2) Dynamic decision optimization: The reward mechanism and experience replay mechanism of RL enable the algorithm to adapt to dynamic scenarios such as fluctuations in medical service volume and policy adjustments;

(3) Discrete optimization adaptation: Aiming at the discreteness of cost allocation coefficients, design a discrete action space and constraint handling mechanism to improve the practical application feasibility of the algorithm.

2) Practical Value

(1) Improve the accuracy of cost accounting: Provide more accurate cost data of departments and service items for public hospitals to support cost control under the DRG/DIP payment reform;

(2) Optimize resource allocation: Guide hospitals to pay attention to the resource allocation of non-direct medical links such as scientific research investment and patient experience through implicit cost alloca tion;

(3) Reduce management costs: The algorithm has a high degree of automation, reducing the cost of expert subjective judgment and manual accounting in traditional methods, and improving the efficiency of cost management.

B. LIMITATIONS AND IMPROVEMENT DIRECTIONS

1) Limitations

(1) Data dependence: The algorithm performance depends on high-quality multi-dimensional cost data. It is difficult to collect implicit cost data (such as patient waiting costs) in some public hospitals;

(2) Graph structure construction: The correlation edge weights between costs and allocation objects are calculated based on historical data, which may have lag;

(3) Algorithm complexity: The GNN-RL model has many parameters and has certain requirements for hard ware computing resources.

2) Improvement Directions

(1) Data augmentation: Combine transfer learning to train the model with a small amount of high-quality data to adapt to hospital scenarios with incomplete data;

(2) Dynamic graph update: Introduce Temporal Graph Neural Networks (T-GNN) to update the edge weights of the graph structure in real time and improve dynamic adaptability;

(3) Model lightweight: Adopt model compression technologies (such as pruning and quantization) to reduce the algorithm's dependence on hardware and facilitate promotion in small and medium-sized hospitals.

VI. CONCLUSION

To address the insufficient accuracy of multi-dimensional cost allocation in public hospitals, this paper proposes a GNN-RL hybrid strategy discrete optimization algorithm . This approach ensure that every dimension of hospital expenditure is accurately mapped and optimized within the financial framework.

1) By constructing a 12-indicator system covering direct, indirect, and implicit costs, using GNN to mine the complex correlation features between cost elements and allocation objects, and combining RL to realize the learning of optimal allocation strategies in dynamic environments.

2) Empirical results show that the average absolute error rate of the algorithm is only 3.27%, which is 18.7% lower than the traditional ABC method, and it performs excellently in dynamic adaptability and allocation fairness.

In the future, the model structure can be further optimized to improve data adaptability and algorithm lightweight levels, mirroring the high-efficiency standards of automated production to promote the wide application of intelligent algorithms in the cost management of public hospitals. This refinement ensures that hospital financial systems achieve the same seamless integration and durability found in high-tech functional fabrics, facilitating a robust digital transformation of medical resource allocation.

AUTHOR CONTRIBUTIONS

Conceptualization –Ling Xu, Han Zhang and Xinhao Zhu; methodology – Ling Xu, Han Zhang and Xinhao Zhu; investigation – Ling Xu, Han Zhang and Xinhao Zhu; writing-original draft preparation – Ling Xu, Han Zhang and Xinhao Zhu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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