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Operationalizing game-theoretic weighting in public hospital cost control: an implementation framework from Chinese tertiary hospitals

Zhihao Yu[1], Guangning Sun[2], Shuaijun Lin[1], Haoqian Hu[1] and Jing Xu[3*]

Abstract

Objective In the current cost management model of public hospitals, decision-making heavily relies on the subjective judgment of managers, resulting in a 12.9% cost overrun compared to the budget in 2020 at a tertiary hospital in Eastern China. To address the systemic issues in the hospital's cost control practices, this study introduced a decision-making framework based on the Game-Theoretic combination weighting method into the hospital's cost management system. By harmonizing expert subjective judgments with objective data dispersion, the framework aims to mitigate subjective biases in hospital cost control, address deficiencies in the top-level design of existing public hospital cost control strategies, and provide a more scientific and systematic cost management approach for public hospitals.

Method Utilizing a literature review and the Delphi method, we established a Cost Control Evaluation Index System specifically tailored for the case hospitals. By employing the Analytic Hierarchy Process (AHP) and the Entropy Weight Method (EWM), we discerned subjective and objective weights for each index. These weights were then amalgamated using a game theory-based combined weighting method. Based on the calculations of weighting in game theory, a cost control optimization scheme for public hospitals was designed and implemented in the case hospital for a duration of three years. Ultimately, the improvement effects before and after the implementation of the optimization scheme were assessed using the fuzzy comprehensive evaluation method.

Results Research indicates previous studies underestimated the importance of indicators such as Logistics Supplies, Utilities (Water, Electricity, Heating), and Disposal Phase, while overemphasizing Salaries, Bonuses, and Maintenance Phase. This study recalibrated indicator weights and optimized strategies accordingly. Three years after implementing this plan, the case hospital demonstrated significant improvements in personnel expenses, material costs, drug costs, administrative expenses, and capital expenditures, with its overall satisfaction score increasing from 79.5656 to 90.2492. Notably, the most substantial improvements occurred in areas where weights were significantly increased, yielding higher returns.

Conclusion During the implementation at the case hospital, the game theory-based combined weighting method proved effective in optimizing cost control strategies for public hospitals. It facilitated more targeted interventions in weak areas of cost management and helped reduce decision-making biases. Additionally, this method

*Correspondence:
Jing Xu
xujinghm@126.com
Full list of author information is available at the end of the article

enhanced the rigor and efficiency of cost control while providing a systematic framework to support decision-making in the medical field.

Keywords Cost control, Decision optimization, Game-theoretic combined weighting method, Fuzzy comprehensive evaluation method

Introduction

In organizational management, cost control is crucial. It focuses on precisely allocating and optimally utilizing key resources such as manpower, materials, and finances. The goal is to maximize economic benefits and promote sustainable, robust organizational growth [1]. Hospitals, unlike other sectors, must be particularly vigilant about biases in cost control decisions because these directly impact patient health [2]. The significant repercussions of consumables and pharmaceuticals in healthcare underscore the need for meticulous cost management. Moreover, information asymmetry often characterizes the relationship between hospital administrators and clinical practitioners [3]. Removed from front-line medical operations, administrators might inadvertently prioritize financial concerns over the complex needs of medical practice. Therefore, hospitals must work to minimize subjective biases and use methods that emphasize objectivity and scientific rigor to evaluate and optimize cost control decisions, thus maintaining the highest quality and safety standards in medical services.

Currently, many hospitals across different provinces and municipalities in China use the Delphi method for making cost decisions. Meanwhile, some less developed hospitals rely solely on managerial discretion without any formal decision method. This trend is particularly pronounced in county-level hospitals [4–6]. Consequently, the development of hospital cost decision-making methodologies that integrate empirical objectivity with contextual rationality has become imperative. The academic exploration of weight determination in decision models has followed an evolutionary trajectory, progressing from subjective weighting approaches to integrated frameworks that reconcile both subjective expertise and objective data analytics. Early studies were dominated by subjective weighting methods. The Analytic Hierarchy Process (AHP) proposed by Saaty [7] in 1977 quantifies the relative importance between criteria through constructing judgment matrices, becoming a mainstream method in healthcare and engineering fields. However, AHP's reliance on expert experience makes it susceptible to cognitive biases. To address this, scholars developed improved methods such as the Best–Worst Method (BWM), which nevertheless cannot overcome the inherent limitations of subjective methods [8]. Meanwhile, data-driven objective weighting methods began to emerge. Based on Shannon's entropy theory [9], the Entropy Weight Method (EWM) was proposed to measure the dispersion degree of indicator data through information entropy. However, the complete neglect of decision-maker preferences in purely objective methods has sparked controversy. Boix-Cots et al. [10] pointed out in their review of weight-based multi-criteria group decision-making methods that complete reliance on data may lead to disconnection between weights and strategic objectives. Subsequently, subjective–objective combined weighting became a research focus. As an early attempt, the linear weighted method integrates subjective and objective weights by setting fixed proportional coefficients [11]. However, due to the implicit correlations and competition between certain indicators in public hospital costs (such as the trade-off between equipment procurement funds and maintenance funds), static weight allocation tends to deviate from actual management needs, making this method unsuitable for our study. The emergence of game-theoretic combined weighting methods marks a methodological breakthrough, with its core being the realization of weight synergy optimization through cooperative game models [12]. Current research has derived various combination paradigms: subjective weighting methods construct weights through expert experience, mainly including Analytic Hierarchy Process (AHP), Best–Worst Method (BWM), and Stepwise Weight Assessment Ratio Analysis (SWARA), etc.; objective weighting methods generate weights based on data statistical characteristics, covering Entropy Weight Method (EWM), Criteria Importance Through Intercriteria Correlation (CRITIC), Logarithmic Percentage Change-driven Objective Weighting (LOPCOW), and Criterion Impact Loss (CILOS), etc. These two categories can be flexibly cross-combined through game-theoretic models.

However, these methods exhibit varying degrees of limitations in public hospital cost control scenarios. In subjective weighting methods, the BWM struggles to accommodate asymmetric relationships within cost systems (e.g., the inherent incomparability between pharmaceutical costs and service quality) due to its dependence on cross-dimensional comparisons of "best–worst" indicators, resulting in distorted weight allocations [13]. SWARA assumes experts can precisely quantify stepwise ratios, but cognitive differences among multiple stakeholders (e.g., healthcare insurance, clinical departments, administration) regarding "importance ratio thresholds" easily cause cumulative errors through progressive addition [14]. In objective weighting methods, CRITIC tends to confuse rational negative correlations (e.g., reverse optimization between staffing costs and outsourcing costs) with random noise (e.g., accidental negative correlation between equipment maintenance fees and patient satisfaction without logical connection), generating counterintuitive weights [15]. LOPCOW tends to exhibit a lagged response to sudden cost changes caused by policy mutations (e.g., abrupt changes in medical insurance policies), as its algorithm relies on fixed time-window historical data smoothing processing, resulting in weight allocations that cannot timely reflect sudden cost restructuring triggered by inspections [16]. CILOS's dependence on indicator independence assumptions easily overlooks hospital cost interactions (e.g., reducing equipment procurement costs may increase maintenance costs to some extent) [17].

The complexity of the cost control system in public hospitals is characterized by an asymmetric relational structure among indicators, high sensitivity to exogenous policies, and strong implicit correlations between indicators, including multidimensional hidden interactions. In comparison, AHP isolates heterogeneous indicators in different levels through hierarchical structures and relative importance scaling, allowing decision-makers to indirectly establish logical connections between asymmetric indicators through intermediate criteria. It aggregates multi-stakeholder opinions through multiple independent assessment rounds while setting consistency checks to automatically identify major disagreements, avoiding linear error accumulation [18]. The Entropy Weight Method determines weights through data dispersion degree, evading correlation misjudgment. EWM spontaneously enhances weight significance of indicators through entropy reduction when inter-indicator interactions cause data distribution variations, thereby achieving dynamic response to implicit correlations [19]. The game-theoretic combined weighting method innovatively coordinates multi-objective conflicts through dynamic game mechanisms that abandon static assumptions of preset ideal solutions. It retains AHP's hierarchical analytical capabilities while utilizing EWM to mine data implicit patterns. Its flexible weighting mechanism simultaneously responds to policy orientations and captures implicit data correlations [20], making it a highly suitable approach for addressing the multi-objective, policy-dependent, and highly complex cost systems of public hospitals. Therefore, this study employs a game theory-based multi-criteria decision-making method, using a Tertiary hospital in China as a pilot case. The aim is to establish a more reasonable and practical cost control indicator system and weight allocation framework for the case hospital, while verifying the applicability of the game theory-based combined weighting method in hospital cost management.

Our research steps are as follows: Through literature review and expert interviews, we identified the core elements of cost control in public hospitals and developed a set of cost control indicators that align with the current requirements for cost management in public hospitals. We then employed the AHP and the EWM to determine both objective and subjective weights for each index. The composite weights of these indices were computed using the game-theoretic combined weighting method to reduce inherent subjective biases in weight determination [21, 22]. Based on the assignment of indicator weights, we formulated a series of optimization strategies related to cost control in public hospitals and implemented them in a tertiary hospital over three years. Finally, leveraging the Fuzzy Comprehensive Evaluation Method, we assessed the effects pre- and post-implementation, validating the efficacy of the optimization strategy and the practicality of the game-theoretic combined weighting method in evaluating cost control in public hospitals.

Method

Analytic hierarchy process

The AHP, developed by Thomas L. Saaty, is a decision-making tool designed to address complex, multi-criteria decision-making issues [23, 24]. AHP primarily focuses on deriving subjective weights for various criteria, effectively translating individual preferences into quantifiable values. Decision-makers employ this methodology to create a hierarchical model that systematically breaks down and assigns weights to various aspects of the decision-making process. The fundamental approach involves decomposing the problem into three hierarchical levels: objectives, criteria, and alternatives. Through pairwise comparisons, decision-makers can ascertain the relative importance of each element, which leads to the formulation of a judgment matrix. This matrix is subsequently used to calculate the subjective weights for each element. The pivotal formulas involved in this process are as follows:

(1) Pairwise comparison matrix:

$$A\omega = \lambda_{\max}\omega$$

(2) Consistency check:

$$M_{CI} = \frac{\lambda_{max} - n}{n - 1}$$

(3) To ensure the consistency of the expert judgment matrix, a consistency test is required. The key formula for this test is [25]:

$$M_{CR} = \frac{M_{CI}}{M_{RI}}$$

where λ_{max} is the maximum eigenvalue of the judgment matrix, and n is the order of the matrix. To ensure the rationality of the decision, the M_{CR} value should be less than 0.1.

Entropy weighting method

The EWM is an objective weighting technique based on information entropy theory, used to determine the weights of criteria in multi-criteria decision analysis. This method evaluates the dispersion of data for each criterion by calculating its information entropy, thereby determining the weights of the indicators. By offering an objective method for calculating weights, this method effectively minimizes subjective biases in the decision-making process [26]. This method quantifies the dispersion degree of each criterion by calculating its entropy value, subsequently determining its objective weight. The core steps are as follows:

1) Build an evaluation matrix B:

$$B = \left(b_{ij}\right)_{m\times n} = \begin{bmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & & \vdots \\ b_{m1} & \cdots & b_{mn} \end{bmatrix}$$

2) Normalize a matrix:

$$x'_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

3) Information entropy value of each index:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} x'_{ij}\ln x'_{ij}$$

4) The information utility value of each index:

$$d_j = 1 - e_j$$

5) Get the objective weight of each index:

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

Game-theoretic combined weighting method

Method description

The Game-Theoretic Combined Weighting Method integrates traditional weighting techniques with game-theoretic to optimize the evaluation criteria weights. This approach utilizes game theory principles to analyze strategic interactions and conflicts among various criteria, enabling a more balanced and effective weight distribution. By combining subjective assessment methods such as the AHP with objective data techniques like the EWM, this method dynamically adjusts weights according to the competitive and cooperative relationships among the criteria. The pivotal formulas involved in this process are as follows:

(1) Initiate the primary weight vector set as $W_q = \{\omega_1, \omega_2, \ldots, \omega_n\}$ ($q = 1,2,\ldots,p$)[27]. In this context, ω denotes the weight vector determined by the p-th weighting method, where n represents the number of index and p is the total number of weighting methods. In this study, the Analytic Hierarchy Process (AHP) and the Entropy Weight Method (EWM) are combined to derive comprehensive weights for the index, thus p = 2. Let $\alpha = \{\alpha1,\alpha2\}$ represent the linear combination coefficients. The linear combination of the two weight vectors is expressed as:

$$W = \alpha_1\omega_1^T + \alpha_2\omega_2^T$$

(2) Based on the idea of the game aggregation model, the two linear combination coefficients are optimized with the goal of minimizing deviation to obtain the most satisfactory weights in W. The objective function is established as:

$$min\left\|\sum_{p=1}^{n}\alpha_p\omega_p^T - \omega_p\right\|_2$$

(3) This equation is equivalently transformed into a system of linear equations based on the first-order derivative conditions for optimization:

$$\begin{bmatrix} \omega_1\omega_1^T & \omega_1\omega_2^T \\ \omega_2\omega_1^T & \omega_2\omega_2^T \end{bmatrix}\begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} \omega_1\omega_1^T \\ \omega_2\omega_2^T \end{bmatrix}$$

(4) To proceed with normalization, α_1 and α_2 are transformed as:

$$\begin{cases} \alpha_1{\prime} = \frac{\alpha_1}{\alpha_1+\alpha_2} \\ \alpha_2{\prime} = \frac{\alpha_2}{\alpha_1+\alpha_2} \end{cases}$$

(5) Finally, the comprehensive weight calculation formula for the indicators is:

$$W = \alpha_1{\prime}\omega_1^T + \alpha_2{\prime}\omega_2^T$$

Numerical example

To demonstrate the computational procedure of the game-theoretic combined weighting method, we randomly initialize the subjective weights ω_1 and objective weights ω_2 for four indicators as follows:

$$\omega_1 = (0.0930, 0.2764, 0.0932, 0.5374), \omega_2 = (0.3600, 0.3589, 0.1868, 0.0943)$$

1) Calculation of Parameters in the Linear Equation System:

$$\omega_1\omega_1^T = (0.0930, 0.2764, 0.0932, 0.5374)\begin{pmatrix} 0.0930 \\ 0.2764 \\ 0.0932 \\ 0.5374 \end{pmatrix} = 0.3825$$

Similarly, the following results can be obtained:

$$\omega_1\omega_2^T = \omega_2\omega_1^T = 0.2008, \omega_2\omega_2^T = 0.3022$$

2) Substituting into the system of linear equations, it follows that:

$$\begin{pmatrix} 0.3825 & 0.2008 \\ 0.2008 & 0.3022 \end{pmatrix}\begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} = \begin{pmatrix} 0.3825 \\ 0.3022 \end{pmatrix}$$

The result is calculated as:

$$\alpha_1 = 0.7295, \alpha_2 = 0.5153$$

3) Normalization is then performed:

$$\begin{cases} \alpha_1\prime = \frac{0.7295}{0.7295+0.5153} \\ \alpha_2\prime = \frac{0.5153}{0.7295+0.5153} \end{cases}$$

It is obtained that:

$$\alpha_1\prime = 0.5860, \alpha_2\prime = 0.4140$$

4) The comprehensive weights of each indicator are:

$$W = 0.5860\begin{pmatrix} 0.0930 \\ 0.2764 \\ 0.0932 \\ 0.5374 \end{pmatrix} + 0.4140\begin{pmatrix} 0.3600 \\ 0.3589 \\ 0.1868 \\ 0.0943 \end{pmatrix} = \begin{pmatrix} 0.2035 \\ 0.3105 \\ 0.1320 \\ 0.3540 \end{pmatrix}$$

Fuzzy comprehensive evaluation method

The fuzzy comprehensive evaluation method is a multi-factor decision analysis approach based on fuzzy mathematics. This method establishes a set of evaluation criteria and constructs a fuzzy relation matrix, transforming qualitative assessments into quantitative analysis. It effectively addresses the inherent fuzziness and uncertainties in the evaluation process, providing a more objective and comprehensive assessment [28, 29]. In this study, the fuzzy comprehensive evaluation method was primarily used to compare and analyze the performance of various cost control indicators before and after the implementation of the optimization plan in the hospital. The specific operational details are as follows:

(1) Construct the evaluation set V and assign corresponding values to each evaluation level.

(2) Determine the weight vector W for each criterion based on their relative importance, ensuring that the influence of each criterion is appropriately reflected in the evaluation. The weight vector is denoted as $W_m = [\omega_{m1}, \omega_{m2}, \ldots, \omega_{mn}]$, where m represents the level of the weight vector, and n is the number of criteria.

(3) Engage domain-specific experts to conduct evaluations and, based on the scores provided by these experts, establish a fuzzy evaluation matrix N_m that reflects the membership degree of each criterion at different evaluation levels. The matrix example is as follows:

$$N_m = \begin{pmatrix} X_{11} & \cdots & X_{1y} \\ \vdots & & \vdots \\ X_{x1} & \cdots & X_{xy} \end{pmatrix}$$

In the given equation, m represents the level of the weight vector, X signifies the membership degree of distinct comments, x stands for the number of indices encompassed in the m level, and y pertains to the count of subsets within the comment set.

(4) Calculate the weight vector for the criterion layer by utilizing the assessment results from the sub-criteria layer. The weight vector of the criterion layer pertaining to the design scheme is computed as:

$$n_m = W_m N_m$$

n_m is the result of multiplying the weight vector W_m with the fuzzy evaluation matrix N_m.

(5) Construct the criterion-level evaluation matrix:

$$n = \begin{pmatrix} n_1 \\ \vdots \\ n_m \end{pmatrix} = \begin{pmatrix} W_1N_1 & \cdots & W_mN_1 \\ \vdots & & \vdots \\ W_1N_m & \cdots & W_mN_m \end{pmatrix}$$

(6) Calculate the comprehensive evaluation weight vector:

$$H = W_m n$$

H represents the comprehensive evaluation weight vector that integrates weights across all evaluation criteria.

(7) Based on this, the total score P of the relevant evaluation is obtained:

$$P = HV$$

Case study

Construction of the cost control evaluation index system for public hospitals

Due to the complexity of cost control in public hospitals, this study first conducted a comprehensive analysis of relevant literature on hospital cost management [30–33], identifying a total of 34 indicators. To thoroughly assess and summarize the various aspects of cost control, the criteria were categorized into five levels: personnel expenses, material costs, drug costs, administrative expenses, and capital expenditures. Overlapping indicators identified in different studies were consolidated or eliminated; for example, "high-cost pharmaceuticals" and "specialized medical equipment" were categorized collectively under "high-value consumables." Additionally, secondary indicators with minimal impact on cost control, such as "public relations expenses" and "non-core departmental activities," were removed. Subsequently, using the Delphi method, six experts from the fields of healthcare management, financial planning, and clinical operations were consulted through multiple rounds of feedback. This process ultimately refined the set to 22 key indicators, which together form the cost control indicator system for public hospitals. Refer to Fig. 1 for a detailed representation.

Weighting of evaluation indices for cost control in public hospitals

Subjective weighting based on the AHP

For the cost control evaluation system in public hospitals, which includes five primary and twenty-two secondary indicators, this study initially invited 18 experts in hospital cost management. During data collection, questionnaires were distributed to these experts, and 14 completed responses were retrieved for use in the AHP.

Due to the potential impact of subjective perception differences among experts on the results, a consistency analysis was conducted on the judgment matrices formulated by fourteen experts. Among them, twelve experts passed the consistency test, with MCR values below 0.1, indicating that the results meet the consistency criteria. Two experts did not pass, and the datasets that failed the test were manually removed. Ultimately, twelve experts provided valid, comparatively scored responses for each indicator. To ensure standardization and uniformity, all participants were contacted via email and asked to complete the questionnaire within a designated time frame. All questionnaires were distributed through the same online platform to maintain consistency during the data collection process.

The selection of experts was based on a rigorous and multidimensional set of criteria to ensure the objectivity and scientific integrity of the evaluations. Experts from the case hospital were deliberately excluded to avoid potential biases linked to personal sentiments or conflicts of interest. The 12 chosen experts possess extensive experience in healthcare management or financial planning and have made significant contributions to cost control in public hospitals. Among them, six hold doctoral degrees in public health or healthcare management, and nine have over 15 years of experience in hospital administration or policy planning. Additionally, several experts have been involved in national healthcare policy assessments or major hospital cost control projects and have published their findings in peer-reviewed international journals.

This procedure aimed to ascertain the relative importance between the criteria and sub-criteria layers, deducing the associated judgment matrix. By adopting the arithmetic mean approach, expert evaluations were consolidated. The AHP was then employed to analyze the cost control indices for public hospitals, resulting in the extraction of the subjective weight vector set ω1 for cost control indicators. Refer to Table 1 for result details.

Objective weighting based on the entropy weight method

Eight experts specializing in hospital cost control were invited to score the criteria layer and sub-criteria layer indices. To ensure the fairness and accuracy of the selection data, we strictly adhered to the same established criteria as before. Additionally, to avoid influence from prior evaluations, we specifically invited eight independent experts who were not part of the original evaluation committee to participate in the selection process. Based on the scoring results, an evaluation matrix was constructed. By integrating the EWM calculation formula, the objective weight vector set ω2 for each index was derived. Refer to Table 2 for details.

Comprehensive weight calculation results based on the game-theoretic combined weighting method

By integrating the results from both subjective and objective weight calculations and employing the relevant formulas of the Game-Theoretic Combined Weighting Method, the comprehensive weights for indices based on game-theoretic combination allocation were obtained. These weights serve as reference standards for constructing the evaluation scheme. The results can be found in Table 3.

Details of the optimization scheme design and implementation

Considering the aforementioned data analysis results, this study formulated a series of cost management optimization schemes. These schemes were subsequently implemented in a tertiary hospital over a three-year

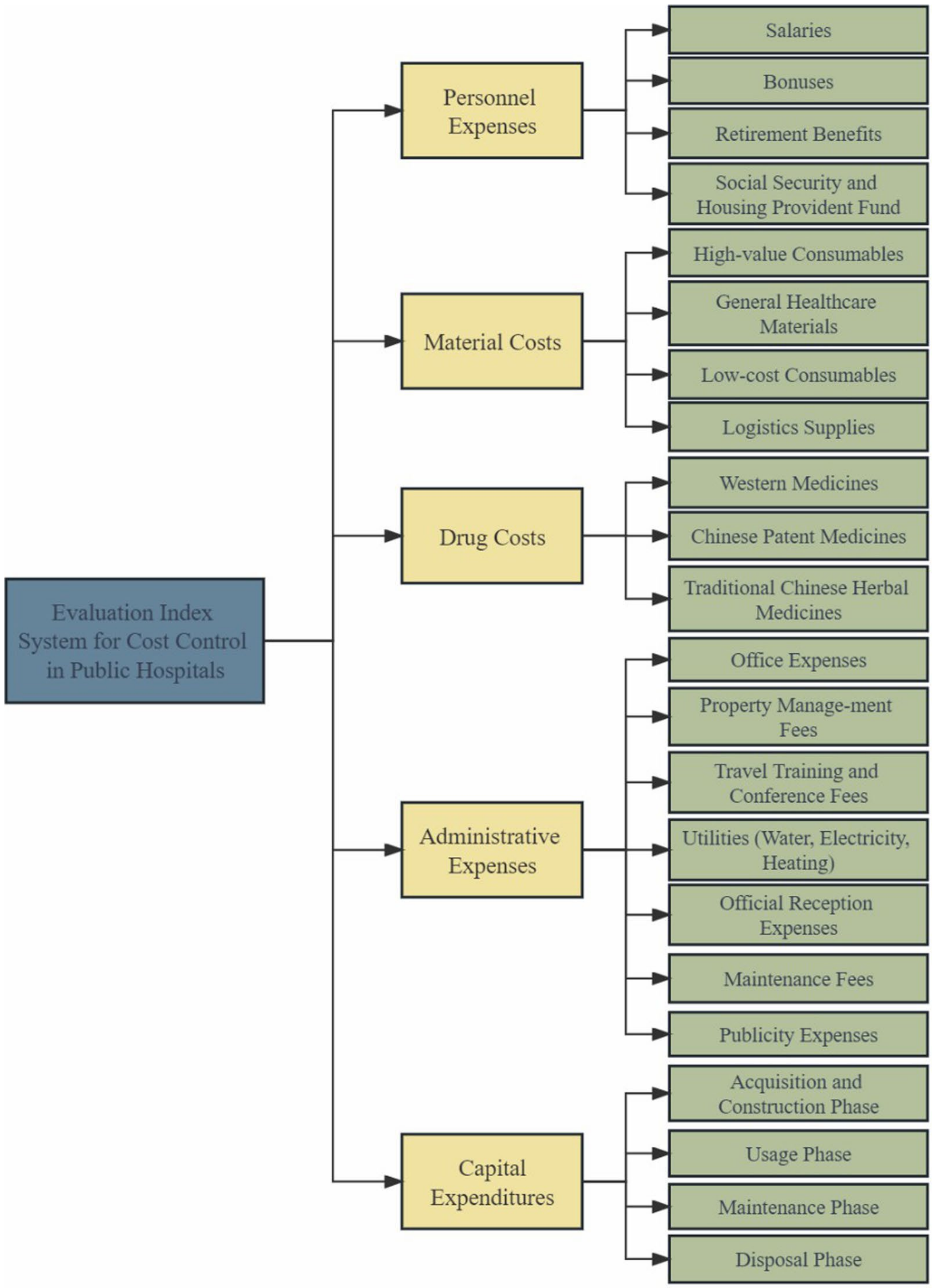

Fig. 1 Evaluation index system for cost control in public hospitals

period. The case hospital, with over 60 years of history, is a Grade III Class A public maternity institution, recognized as achieving the highest accreditation within the national healthcare system, exemplifying superior standards in medical services, ethics, and healthcare delivery. Amid a societal trend of declining childbirth rates among women of childbearing age, the hospital faced significant operational challenges. In 2020, the hospital experienced significant budget overruns across various cost categories. The overall costs exceeded the budget by 12.9%,

Table 1 Subjective weights of indices

Index	B1	B2	B3	B4	B5	Subjective weight
A	0.2232	0.1691	0.1282	0.2563	0.2232	
C1	0.3270					0.0730
C2	0.3618					0.0807
C3	0.1477					0.0330
C4	0.1635					0.0365
C5		0.4179				0.0707
C6		0.2485				0.0420
C7		0.2246				0.0380
C8		0.1090				0.0184
C9			0.4126			0.0529
C10			0.3275			0.0420
C11			0.2599			0.0333
C12				0.0921		0.0236
C13				0.2154		0.0552
C14				0.1239		0.0317
C15				0.1951		0.0500
C16				0.1368		0.0351
C17				0.1368		0.0351
C18				0.0999		0.0256
C19					0.3407	0.0760
C20					0.2025	0.0452
C21					0.2865	0.0640
C22					0.1703	0.0380

with personnel expenses surpassing the budget by 14.2%, material costs showing the highest overrun at 19.3%, and administrative expenses exceeding the budget by 18.1%. Additionally, capital expenditure increased substantially compared to previous years due to the implementation of hospital expansion projects. The convergence of multiple factors led to a significant escalation in the hospital's overall costs, posing severe challenges to cost management. With limited revenue growth, cost control has become a critical measure for sustaining operations. From March 2020, the hospital began aligning its actions with index weights derived from the game-theory-based combined weighting method. By comparing these weights with previous years and consulting relevant literature [34–37], the hospital adjusted its cost control scheme as detailed below:

For personnel expenses, the weight assigned to salaries and bonuses has significantly declined compared to previous years. In response, the hospital selectively increased salaries for key roles and top performers to enhance retention and motivation. A human resource management system was implemented to optimize staffing and scheduling through comprehensive data analysis, aiming to improve overall efficiency. Flexible work arrangements were also adopted, adjusting staff allocation and working hours based on departmental workload and task nature.

In managing material costs, high-value consumables have consistently represented a significant proportion and remain key focus areas. Recent calculations indicate that their current weight has further increased compared to previous years. Consequently, control measures have been intensified, including the implementation of barcode management to track consumable usage and real-time inventory monitoring through information technology, ensuring timely replenishment and proper handling of expired items. Additionally, the hospital optimized medical resource distribution routes and timing to reduce transportation time and costs. Moreover, we found that the weight of logistics supplies has significantly increased compared to previous evaluations. In response, we have optimized the procurement process, enhanced inventory control to reduce waste and overstocking, and implemented real-time tracking systems to improve visibility and efficiency. Additionally, we have established stricter supplier evaluation criteria and performance monitoring mechanisms to ensure high-quality and timely delivery of logistics supplies.

For drug costs, the slight decrease in the weight assigned to pharmaceuticals led the hospital to adopt a

Table 2 Objective weights of indices

Index	Information entropy value	Information utility value	Weight
C1	0.589	0.411	0.03283
C2	0.356	0.644	0.05146
C3	0.834	0.166	0.01327
C4	0.834	0.166	0.01327
C5	0.002	0.998	0.07979
C6	0.356	0.644	0.05146
C7	0.387	0.613	0.04895
C8	0.388	0.612	0.04891
C9	0.589	0.411	0.03283
C10	0.581	0.419	0.03350
C11	0.614	0.386	0.03087
C12	0.581	0.419	0.03350
C13	0.356	0.644	0.05146
C14	0.388	0.612	0.04891
C15	0.003	0.997	0.07968
C16	0.356	0.644	0.05146
C17	0.356	0.644	0.05146
C18	0.581	0.419	0.03350
C19	0.003	0.997	0.07968
C20	0.589	0.411	0.03283
C21	0.356	0.644	0.05146
C22	0.388	0.612	0.04891

dual strategy of resource expansion and cost reduction. Standardized protocols for drug use and procurement were established to minimize waste and prevent over-purchasing. Training on proper medication practices was provided to medical staff to ensure accurate dispensing. The hospital also streamlined drug budgeting and approval processes, reducing regulatory manpower costs.

In managing administrative expenses, the weight of utilities, including water, electricity, and heating, significantly increased. The hospital enhanced oversight by establishing transparent assessment and feedback mechanisms, improving the supervision of administrative funds. The Game-Theoretic Combined Weighting Method was introduced to reduce the subjectivity of experiential decision-making, minimizing decision discrepancies.

Regarding capital expenditures, the significance of the disposal stage has significantly increased compared to previous evaluations. In response, we have implemented stricter waste classification and disposal procedures to ensure compliance with environmental regulations. Additionally, the significance of the maintenance phase has significantly decreased compared to previous phases. In response, we have enhanced monitoring and evaluation systems, optimized resource allocation, introduced a preventive maintenance strategy, and provided continuous training for maintenance staff to improve efficiency and minimize unexpected disruptions.

Comprehensive evaluation based on fuzzy comprehensive evaluation method

Fuzzy comprehensive evaluation results of cost control for the case hospital in 2020

Utilizing the established public hospital cost control index system and its associated weights, we conducted a comprehensive assessment of the cost control situation at the case hospital in 2020. The evaluation process is described as follows:

Initialize the evaluation standard set V, which includes: {"Exceptional", "Excellent", "Standard", "Below Standard", "Very Poor"}. The corresponding evaluation values are set as V = {100,80,60,40,20}.

Design and populate the fuzzy comprehensive evaluation matrix for the case hospital's cost control indicators. This step involved inviting ten experts from the field of cost control to provide professional scores for the hospital's cost control measures. Based on these scores and feedback, we calculated the membership degrees of the evaluation language for each index, denoting them as N1-N5. These respectively represent the fuzzy comprehensive evaluation matrices for personnel expenses, material costs, drug costs, administrative expenses, and capital expenditures.

$$N1 = \begin{pmatrix} 0.2 & 0.6 & 0.2 & 0 & 0 \\ 0.2 & 0.8 & 0 & 0 & 0 \\ 0.2 & 0.6 & 0.2 & 0 & 0 \\ 0.1 & 0.8 & 0.1 & 0 & 0 \end{pmatrix}$$

$$N2 = \begin{pmatrix} 0.8 & 0.2 & 0 & 0 & 0 \\ 0.6 & 0.4 & 0 & 0 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \\ 0.5 & 0.4 & 0.1 & 0 & 0 \end{pmatrix}$$

$$N3 = \begin{pmatrix} 0 & 0.1 & 0.6 & 0.3 & 0 \\ 0 & 0.2 & 0.8 & 0 & 0 \\ 0 & 0.1 & 0.8 & 0.1 & 0 \end{pmatrix}$$

$$N4 = \begin{pmatrix} 0.5 & 0.4 & 0.1 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0 & 0 \\ 0.6 & 0.1 & 0.3 & 0 & 0 \\ 0 & 0.3 & 0.6 & 0.1 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \\ 0 & 0.4 & 0.6 & 0 & 0 \\ 0.2 & 0.6 & 0.2 & 0 & 0 \end{pmatrix}$$

$$N5 = \begin{pmatrix} 0.8 & 0.1 & 0.1 & 0 & 0 \\ 0.6 & 0.4 & 0 & 0 & 0 \\ 0 & 0.6 & 0.3 & 0.1 & 0 \\ 0 & 0.2 & 0.8 & 0 & 0 \end{pmatrix}$$

Table 3 Comprehensive weight results

Index	Results from analytic hierarchy process	Results from entropy weight method	Results from game theoretic combined weighting method
C1	0.0730	0.03283	0.0520
C2	0.0807	0.05146	0.0654
C3	0.0330	0.01327	0.0227
C4	0.0365	0.01327	0.0244
C5	0.0707	0.07979	0.0755
C6	0.0420	0.05146	0.0469
C7	0.0380	0.04895	0.0437
C8	0.0184	0.04891	0.0343
C9	0.0529	0.03283	0.0424
C10	0.0420	0.03350	0.0376
C11	0.0333	0.03087	0.0320
C12	0.0236	0.03350	0.0288
C13	0.0552	0.05146	0.0532
C14	0.0317	0.04891	0.0407
C15	0.0500	0.07968	0.0655
C16	0.0351	0.05146	0.0437
C17	0.0351	0.05146	0.0437
C18	0.0256	0.03350	0.0297
C19	0.0760	0.07968	0.0779
C20	0.0452	0.03283	0.0387
C21	0.0640	0.05146	0.0574
C22	0.0380	0.04891	0.0437

Based on this, the total score for the cost control situation of the case hospital in 2020 can be determined as:

$$\mathrm{P} = \mathrm{HV} = 79.5656$$

Fuzzy comprehensive evaluation results for cost control of the case hospital in 2023

Based on the evaluation conducted in 2020, a subsequent assessment of the cost control outcomes was undertaken in March 2023 by the case hospital. The assessment aimed to gauge the effectiveness and ongoing improvements of the cost control measures over the three-year period, as well as to pinpoint areas for further optimization. Mirroring the 2020 evaluation process, the original ten cost control experts were convened to score the cost control scheme of the case hospital. Each expert determined the degree of membership for each review and utilized these scores to construct the fuzzy comprehensive evaluation matrix at the indicator sub-criterion level. Through the fuzzy comprehensive evaluation, fuzzy comprehensive evaluation matrices for each criterion level (N1-N5) were generated.

$$\mathrm{N1} = \begin{pmatrix} 0.2 & 0.7 & 0.1 & 0 & 0 \\ 0.6 & 0.4 & 0 & 0 & 0 \\ 0.8 & 0.2 & 0 & 0 & 0 \\ 0.4 & 0.6 & 0 & 0 & 0 \end{pmatrix}$$

$$\mathrm{N2} = \begin{pmatrix} 0.9 & 0.1 & 0 & 0 & 0 \\ 0.7 & 0.3 & 0 & 0 & 0 \\ 0.6 & 0.4 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 \end{pmatrix}$$

$$\mathrm{N3} = \begin{pmatrix} 0.5 & 0.5 & 0 & 0 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \end{pmatrix}$$

$$\mathrm{N4} = \begin{pmatrix} 0.5 & 0.4 & 0.1 & 0 & 0 \\ 0.5 & 0.4 & 0.1 & 0 & 0 \\ 0.6 & 0.1 & 0.3 & 0 & 0 \\ 0.3 & 0.6 & 0.1 & 0 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \\ 0.4 & 0.6 & 0 & 0 & 0 \\ 0.6 & 0.2 & 0.2 & 0 & 0 \end{pmatrix}$$

$$N5 = \begin{pmatrix} 0.9 & 0.1 & 0 & 0 & 0 \\ 0.6 & 0.4 & 0 & 0 & 0 \\ 0.4 & 0.4 & 0.2 & 0 & 0 \\ 0.6 & 0.4 & 0 & 0 & 0 \end{pmatrix}$$

The overall score for the cost control status of the case hospital in 2023 can be derived as:

$$P = HV = 90.2492$$

Discussion

Taking a tertiary public hospital as a representative case, this study reconstructs the cost control index system through a game theory-based combination weighting method, identifying potential biases in certain traditional static models and their possible implications for hospital strategic decisions. Case data indicates adjusted weights of labor cost indicators decreased moderately (e.g., Salaries from 0.0730 to 0.0520, Bonuses from 0.0807 to 0.0654), which aligns with existing literature observations on AHP's propensity to emphasize explicit labor costs [38]. The proposed model supplements expert experience with entropy-based volatility analysis and policy-aware dynamic negotiation [39], offering an alternative pathway for weight calibration.

The increased weights of logistics operations and certain asset life-cycle indicators (e.g., Utilities from 0.0500 to 0.0655, Disposal Phase from 0.0380 to 0.0437) highlight previously underemphasized areas in hospital cost control. The Logistics Supplies weight adjustment from 0.0184 to 0.0343 may reflect post-COVID-19 emergency storage needs, while also indicating limitations of historical models in capturing interdependencies. Game-theoretic provides one viable approach to quantify cross-departmental influences through coalition analysis.

Policy responsiveness is observed in specific weight adjustments. For Traditional Chinese Herbal Medicines (0.0333 to 0.0320), the entropy method's lower weight (reflecting stability) interacts with AHP's policy-driven higher valuation, suggesting a potential negotiation logic that balances data patterns with policy considerations.

However, the findings of this study must be interpreted within specific constraints. First, the case hospital's well-developed information systems provided high-quality data for the model. In institutions with weaker data collection capabilities, the objectivity of the entropy weight method may be compromised [40]. Second, regional policy differences significantly influence the depth of weight adjustments. For instance, the increased weight of the Disposal Phase heavily depends on the stringency of local environmental regulations. In regions with more lenient policies, the model's sensitivity may be reduced [41].

Comparing the fuzzy comprehensive evaluation results from 2020 and 2023, it is evident that the case hospital has made significant progress in cost control. Indicators such as personnel expenses, material costs, drug costs, administrative expenses, and capital expenditures all showed varying degrees of improvement. Notably, areas that previously had low weights and low scores, such as Maintenance Fees (C17) and Disposal Phase (C22), experienced particularly significant enhancements. These changes suggest potential benefits of the optimization plan in enhancing cost management efficiency and provide preliminary support for the feasibility of the game-theoretic combined weighting method.

Furthermore, in cases where indicator weights were reduced, the hospital adopted more lenient management approaches, yet this did not lead to a decline in evaluation scores, such as drug costs (N3). In fact, most indicators showed improvement, which can be attributed to the revised management policies aligning better with the hospital's operational needs. This outcome further confirms the feasibility and effectiveness of the game-theoretic combined weighting method in cost control, highlighting its ability to dynamically adjust weights based on real-world conditions [42], thereby optimizing resource allocation and enhancing management efficiency.

However, while scores for most indicators have risen, not all have reached the 'Exceptional' or 'Excellent' rating, indicating room for further optimization in specific areas of cost control. It is crucial to recognize that cost control optimization is not an immediate achievement but an ongoing process that requires continuous adjustments [43]. This suggests that the impact of the optimization solutions will extend beyond current results and grow over time. As the healthcare industry evolves rapidly, hospitals must continuously revise and strengthen their cost control strategies to adapt to external changes.

Conclusion

This research, centered on the needs of hospitals, constructs a public hospital cost control indicator system based on the game-theoretic combined weighting method. It addresses redundancy issues among indicators, enhancing the comprehensiveness of the public hospital cost control system. The integration of game-theoretic with weighting methods helps improve the design of cost control, reduces subjectivity in decision-making evaluations, and enhances the rationality of the cost control framework. A case hospital serves as the subject for practical implementation, and its results are assessed comprehensively using the fuzzy comprehensive evaluation method. This assessment provides initial insights into the feasibility of the game-theoretic combined weighting method in cost control.

From a theoretical perspective, this study innovatively introduces Nash equilibrium-based dynamic negotiation into public hospital cost management, adopting a dual-driven weight generation framework that integrates "data" and "policy" dimensions. This framework, through its dynamic game mechanism, abandons the static assumption of predefined ideal solutions, enabling dynamic coordination of multiple objectives. By constructing AHP-based policy constraints and EWM-driven data signatures as dual players in a non-cooperative game, their conflicting weighting preferences are reconciled through Nash equilibrium computation. The framework's elastic weighting mechanism not only responds synchronously to policy directives but also effectively captures implicit data correlations, enhancing both the scientific rigor of cost management and decision-making support capabilities. Through empirical validation, this study provides preliminary evidence of the combined utility of classical decision-making methods in healthcare cost control and offers a replicable implementation paradigm. The framework enriches the methodology of healthcare cost control while offering an empirical model for adaptive governance in scenarios with multiple conflicting objectives. Its dynamic characteristics and dual-driven mechanism are particularly well-suited to addressing the complex management requirements emerging from healthcare system reforms.

From a practical perspective, the value of this study has been preliminarily validated through pilot implementation at a case hospital. Over three years of implementing the optimized weight-based cost control scheme, significant improvements have been observed across core indicators, ranging from personnel expenses, material costs, and drug costs to administrative expenses and capital expenditures. Notably, even in areas where indicator weights were relatively reduced, evaluation scores not only maintained stability but showed positive development trends. More significantly, previously underweighted indicators demonstrated marked improvements in satisfaction scores after their weights were dynamically adjusted to appropriate levels. These results indicate that the dynamic weighting model effectively balances the trade-offs between efficiency and equity, as well as between short-term cost containment and long-term sustainability, proving to be a viable and practically valuable decision-making method for cost management in public hospitals.

To advance cost control research further, future studies should pursue comprehensive exploration across multiple critical directions. The methodology's applicability should be extensively tested across diverse healthcare settings, including secondary hospitals with different resource constraints, specialized facilities such as children's hospitals and cancer centers, rural healthcare institutions, and private medical facilities with distinct management objectives. The framework's adaptability needs thorough examination under varying healthcare environments and policy frameworks, particularly focusing on different insurance systems, regulatory reforms, and degrees of government intervention. Concurrent analysis should evaluate the framework's effectiveness across different healthcare management cultures and explore how cultural factors influence stakeholder engagement. Technological enhancement opportunities deserve significant attention, particularly the integration with artificial intelligence and machine learning algorithms for sophisticated pattern recognition in cost data, incorporation of big data analytics for real-time monitoring, and development of automated decision support systems. Methodological improvements could focus on developing more sophisticated utility functions, incorporating uncertainty analysis, enhancing dynamic adjustment capabilities, and introducing multi-period optimization techniques. Future research could incorporate diverse combined weighting methodologies, such as SOWIA, IDOCRIW and the simple averaging approach, for comprehensive analytical purposes. Through systematic comparative analysis between the computational results of these methods and the current study's findings, researchers can thoroughly evaluate the accuracy of weight determination and potentially identify the specific advantages and limitations of different weighting approaches within particular application contexts. Furthermore, the implementation of cross-validation using multiple weighting methods would contribute to examining the robustness and reliability of research outcomes, thereby providing more scientifically sound and reliable evidence for weight determination procedures. From a practical implementation perspective, emphasis should be placed on establishing standardized guidelines for different hospital types, developing comprehensive information-based cost monitoring systems, and designing effective change management strategies. These research directions collectively aim to enhance the framework's robustness, adaptability, and practical value across diverse healthcare settings while leveraging technological advancements to improve its effectiveness in supporting complex healthcare management decisions.

However, due to the limitations of research perspectives and environmental conditions, this study has certain shortcomings. In constructing the cost control indicator system for public hospitals, the complexity of the system means that the appropriateness of some indicators still requires further exploration. Moreover, since cost control spans multiple sectors and phases, the improvement process includes not only the strategies proposed in this study but might also involve optimization measures from other related fields. The increase in satisfaction from the fuzzy comprehensive evaluation can be seen as a cumulative effect of various factors. Therefore, whether the optimization strategy based on the game-theoretic combined weighting method plays a decisive role in cost control improvement remains to be further studied. These issues will continue to be explored and refined in subsequent research.

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Author contributions
Z.Y. was primarily responsible for the conceptualization, methodology design, data analysis, and drafting of the manuscript. G.S. and S.L. handled data collection and manuscript revisions. H.H. participated in data analysis, validation, and editing. J.X. provided supervision, coordinated the research team, and contributed to the final revisions of the manuscript. All authors reviewed and approved the final manuscript.

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Availability of data and materials
The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
This study involved only anonymous scoring by experts without the collection of any personal identifiable information or sensitive data, so ethical approval was not required. The experts participated voluntarily and anonymously, with their contributions limited to scoring based on the research criteria.

Consent for publication
The authors have obtained consent from the experts who provided the evaluation scores, ensuring their agreement for the use of their anonymized data in this publication.

Competing interests
The authors declare no competing interests.

Author details
[1]Faculty of Humanities and Social Sciences, Macao Polytechnic University, Macao, China. [2]Medical Department, Weifang Maternal and Child Health Hospital, Weifang, Shandong, China. [3]Finance Department, Weifang Mental Health Center, Weifang, Shandong, China.

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