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Research on Dynamic Evaluation Model of Medical Service Quality Based on Proximity Function and Fuzzy Mathematics

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Abstract

This study proposes a dynamic evaluation model for medical service quality that integrates proximity function, fuzzy mathematics, and hexahedral boundary function theory (a mathematical tool that defines the value range of evaluation indicators by setting threshold constraints across six orthogonal dimensions). The method constructs a three-dimensional “past-present-future” data constraint system and a dynamic game weighting mechanism. Expected results based on simulated data demonstrate that the model shows potential for improvement in convergence efficiency and uncertainty reduction, while providing actionable outputs correlated with rating systems for quality control.

Keywords

Medical Service Quality, Dynamic Evaluation Model, Boundary Function, Convergence Efficiency, Fuzzy Mathematics, Proximity Function

1. Introduction

1.1. Research Background

Medical service quality evaluation serves as the core instrument for standardizing clinical practices, optimizing resource allocation, and alleviating physician-patient conflicts [1] [2]. However, its complexity manifests in three critical pain points: First, multi-parameter fuzziness and coupling—core indicators such as "reasonable medical costs" and "quality service duration" lack clear quantitative boundaries, and parameters including costs, duration, and technology promotion are mutually constraining, making independent measurement difficult [3] [4]. Second, temporal dimension limitations—traditional models rely predominantly on historical data retrospection or real-time data snapshots [5] [6] [unable to anchor stable evaluation benchmarks while failing to accommodate the forward-looking needs of medical technology iteration, easily triggering lag bias or overfitting. Third, disconnect between weight design and convergence practice—static equilibrium weights cannot reflect element competitive relationships [1] [7], and most models pursue convergence speed while neglecting the operability and scenario adaptability of convergence results [8] [9].

Existing evaluation methods (such as Analytic Hierarchy Process, TOPSIS method, and Data Envelopment Analysis) have certain applications in multi-indicator integration but all exhibit significant deficiencies: AHP is highly subjective, with weight allocation easily influenced by expert experience [6]; TOPSIS uses fixed ideal solutions as benchmarks, unable to adapt to dynamic medical scenarios [5]; DEA focuses on efficiency evaluation while neglecting patient core needs and technology advancement orientation [3]. The common limitation of these methods lies in the lack of explicit boundary constraint design and dynamic regulation mechanisms, resulting in divergent evaluation results with poor interpretability, making direct guidance of medical quality control practice difficult [4] [10].

The invention patent "Medical Service Quality Control Method and Quality Management Platform System, Electronic Device" [11] provides core ideas for solving the above pain points through breakthrough innovations: proposing the hexahedral boundary function method to construct a "basically determined domain" for medical service value through six orthogonal dimensions; designing a dynamic weight adjustment mechanism to strengthen positive element empowerment; establishing a grade-price linkage system to achieve practical transformation of evaluation results. Based on this foundation, this study integrates proximity function and fuzzy mathematics theory [12] [13], deepening data dimension integration, element weight optimization, and convergence value empowerment to construct a scientifically comprehensive dynamic evaluation model that systematically addresses the core bottlenecks of traditional evaluation.

1.2. Research Significance

1.2.1. Theoretical Significance

This study constructs for the first time a three-dimensional data constraint system of "past-present-future" to address the limitations of traditional evaluation methods in the temporal dimension; establishes a "promotion-hindrance" element dynamic game weight mechanism to compensate for the inherent defects of static weights; and achieves collaborative optimization of convergence efficiency and practical value, enriching the theoretical system of medical service quality evaluation. Simultaneously, the deep integration of hexahedral boundary function with proximity function and fuzzy mathematics provides a new methodology for uncertainty evaluation, expanding the application scenarios of boundary function theory in the medical field [13].

1.2.2. Practical Significance

The value grades output by the model can be directly mapped to medical personnel service fees, institutional charging standards, and medical insurance reimbursement ratios [11], providing real-time quality control tools for medical institutions, quantitative decision-making basis for regulatory departments, and transparent service references for patients. By guiding medical services to converge toward "high technology, high efficiency, low cost," the model can effectively reduce patient medical burden, promote quality technology dissemination, standardize medical service behavior, and support the implementation of the "Healthy China" strategy [3] [4].

1.3. Research Objectives and Content

1.3.1. Research Objectives

To construct a dynamic evaluation model for medical service quality integrating proximity function, fuzzy mathematics, and hexahedral boundary function, achieving full coverage of data dimensions, dynamic element weighting, and operable convergence results, thereby enhancing the scientific rigor, precision, and practical adaptability of evaluation.

1.3.2. Research Content

Theoretical Foundation Integration: Systematically review boundary function, proximity function, and fuzzy mathematics theories, clarifying their adaptability in medical service evaluation;

Model Framework Construction: Design a three-level "input-processing-output" framework, integrating three-dimensional data constraints, dynamic weight optimization, and convergence mechanisms;

Key Step Modeling: Complete mathematical modeling of fuzzy priority quantification, proximity deviation calculation, service value correction, and dynamic grade adjustment;

Logical Verification Analysis: Verify model convergence efficiency, logical consistency, and scenario adaptability through simulated data;

Innovation and Application Prospect Analysis: Deepen model innovation value, clarify practical application paths and future optimization directions.

2. Related Theories and Methodological Foundations

2.1. Progress in Existing Research on Medical Service Quality Evaluation

Medical service quality evaluation has formed multi-dimensional indicator systems, but significant limitations remain at the methodological level: Traditional fuzzy comprehensive evaluation methods can handle parameter fuzziness, but static weighting leads to lack of dynamic adaptability in evaluation [6] [14]; proximity functions have been used for deviation quantification in multi-objective decision-making [3] [7], but have not been effectively combined with the temporal characteristics and boundary constraints of medical services; boundary element methods and finite element methods for convergence efficiency optimization in engineering fields [8] [9] [12] provide reference for the medical field, but require adaptation to the multi-parameter coupling and practice-oriented needs of medical services.

Existing research [1] [10] [15] focuses mostly on single technology applications, lacking multi-theory fusion and full-process optimization, with obvious gaps particularly in data dimension integration, dynamic element weight configuration, and practical transformation of convergence results, providing innovation space for this study.

2.2. Core Theoretical Foundations

2.2.1. Fuzzy Mathematics Theory

Fuzzy mathematics transforms fuzzy concepts such as "reasonable cost" and "quality service" into quantitative descriptions in the [0, 1] interval through fuzzy sets and membership functions [6] [14]. Fuzzy Analytic Hierarchy Process (FAHP) can transform qualitative priorities into quantitative weights, ensuring the scientific rigor of weight allocation through fuzzy judgment matrix construction and consistency testing [6], adapting to the "priority quantification" needs in medical service evaluation.

2.2.2. Proximity Function Theory

The proximity function is used to measure the similarity deviation between evaluation objects and ideal benchmarks. Its core advantage lies in avoiding interference from absolute value fluctuations through relative deviation calculation [3] [7]. The general expression is:

$$D = 1 - \frac{X - X_0}{X + X_0}$$

where, X is the individual parameter value, X_0 is the benchmark value, $D \in [0,1]$, and values closer to 1 indicate higher fitness, adapting to the core logic of "individual vs. system benchmark comparison" in medical services [15].

2.2.3. Boundary Function and Convergence Efficiency Theory

The hexahedral boundary function, as the core constraint tool of this model, essentially defines the reasonable value range of medical service evaluation indicators (such as cost, duration, technology adoption rate) by constructing a mathematical space bounded by six mutually orthogonal dimensions (top, bottom, left, right, historical background, and future prospect surfaces), thereby limiting uncertainty within interpretable intervals.

Boundary functions (domain functions) are constraint tools that define the value range of evaluation objects, limiting uncertainty evaluation within a "basically determined domain" through rigid and flexible combination [9] [12]. The hexahedral boundary function covers the full dimensions of "technology-cost-efficiency-temporal sequence," making it more suitable for multi-parameter constraint needs of medical services than traditional tetrahedral or cubic boundaries [13]. Its convergence mechanism achieves rapid convergence through "hard constraints (bottom-line protection) + soft adjustment (elastic adaptation)" [8] [11].

Core quantitative indicators of convergence efficiency include: convergence steps (number of iteration durations to reach stable domain), intra-domain fluctuation rate (result fluctuation amplitude after stabilization), and boundary fitness (proximity to optimal boundary) [15] [16], providing clear standards for model effectiveness verification.

2.3. Theoretical Adaptability Analysis

The multi-parameter fuzziness, dynamics, and practice-oriented nature of medical service evaluation determine that single theory cannot meet the needs: Fuzzy mathematics solves parameter fuzziness and priority quantification problems; proximity function achieves precise deviation calculation between individuals and benchmarks; hexahedral boundary function constructs multi-dimensional constraint space, improving evaluation convergence efficiency and stability; the fusion of the three forms a full-process theoretical support of "fuzzy quantification-deviation calculation-boundary constraint-dynamic convergence," perfectly adapting to the core needs of medical service quality evaluation [11] [13].

3. Construction of Dynamic Evaluation Model for Medical Service Quality

3.1. Overall Model Framework

The model follows a three-level logic of "input-processing-output," integrating three-dimensional data constraints, dynamic weight optimization, and convergence mechanisms.

3.1.1. Input Layer

Input data includes two types of core information:

Individual Diagnosis and Treatment Data: Evaluation object (medical personnel/institution/group) ID associated diagnosis and treatment cost C_i (yuan), treatment duration Z_i (days), academic promotion adoption rate T_i (%), system parameter O_i (management compliance score);

System Benchmark and Boundary Data: System average diagnosis and treatment cost for the same period $\mu_C = \sum C_n / n$, average treatment duration $\mu_C = \sum C_n / n$, maximum adoption rate of new diagnosis and treatment methods $T_{\max}^{\text{new}} = \max\left(T_{\text{new}}\right)$ (ceiling boundary), shortest reasonable duration $Z_{\min}$, lowest reasonable cost $C_{\min}$ (right boundary), historical data mean μ 与 σ (background function), future predicted value P (prospect function), where n is the total number of evaluation objects for the same period.

3.1.2. Processing Layer

Core processing procedures include four steps:

Fuzzy Priority Weight Quantification: Transform qualitative priorities of "social average > academic promotion > system" into quantitative weights through FAHP;

Proximity Deviation Calculation: Calculate proximity of each parameter to benchmarks combining hexahedral boundary constraints;

Service Value EV Fuzzy Correction: Obtain service value by integrating proximity and weights through fuzzy synthesis operators;

Dynamic Grade Adjustment: Achieve grade promotion or demotion through fuzzy rules based on continuous period EV values.

3.1.3. Output Layer

Output medical service value grades (Grade A to Grade E) and associated price systems (medical personnel service fees, institutional charging standards, medical insurance reimbursement ratios), achieving "grade-price" linkage [11].

3.2. Key Step Mathematical Modeling

3.2.1. Step 1: Fuzzy Priority Weight Quantification

The patent explicitly states "social average priority (duration, cost) > academic promotion priority (adoption rate) > system priority (management compliance)" [11], realized through FAHP quantification:

Construct Fuzzy Judgment Matrix: Transform priorities into [0, 1] interval membership degrees, where matrix element r_{ij} represents the priority of parameter i relative to j, satisfying $r_{ij} + r_{ji} = 1$. The matrix is as follows:

$$R = \begin{bmatrix} 1.0 & 0.6 & 0.8 & 0.9 \\ 0.4 & 1.0 & 0.3 & 0.7 \\ 0.2 & 0.7 & 1.0 & 0.8 \\ 0.1 & 0.3 & 0.2 & 1.0 \end{bmatrix}$$

(Parameter 1: Treatment duration Z; Parameter 2: Academic promotion adoption rate T; Parameter 3: Diagnosis and treatment cost C; Parameter 4: System parameter O)

Consistency Testing and Weight Calculation: After testing, the matrix meets consistency requirements ($CI < 0.1$). Using the weighted average method, the weight coefficients are obtained: $K_1 = 0.35$ (duration), $K_2 = 0.20$ (adoption rate), $K_3 = 0.30$ (cost), $K_4 = 0.15$ (system parameter), satisfying the logic of $K_1 > K_3 > K_2 > K_4 > 0$.

3.2.2. Step 2: Proximity Calculation Based on Hexahedral Boundary

Combining the patent hexahedral boundary function [11], design differentiated proximity functions to ensure parameters converge within the "basically determined domain":

Boundary Constraint Preprocessing:

Academic promotion adoption rate T: *If* $T > T_{\max}^{\text{new}}$, truncate to $T_{\max}^{\text{new}}$ (ceiling constraint);

Treatment cost C: *If* $C > 1.5\mu_C$ (hindrance threshold), decay according to $C' = C \times \exp\left(-0.2\left(C - 1.5\mu_C\right)\right)$ ($\lambda = 0.2$).

Proximity Function Design:

Academic Promotion Proximity (with ceiling boundary, promotion element):

$$D_T = \frac{T}{T_{\max}^{\text{new}}} \times \omega P \quad (\omega P = 1.2 \text{ ceiling boundary weight})$$

This design strengthens technology innovation empowerment. When $T = T_{\max}^{\text{new}}$, $D_T = 1.2$, reflecting excess reward logic [13] [15].

Treatment Duration Proximity (with right boundary and hindrance boundary):

$$D_Z = \begin{cases} 1 - \dfrac{Z - Z_{\min}}{Z_{\text{threshold}} - Z_{\min}} & \left(Z_{\min} \le Z \le Z_{\text{threshold}}\right) \\ \exp\left(-0.3\left(Z - Z_{\text{threshold}}\right)\right) & \left(Z > Z_{\text{threshold}}\right) \end{cases}$$

where $Z_{\text{threshold}} = 1.5\mu_Z$ (hindrance threshold), $Z_{\min}$ is the shortest duration of clinical pathway, balancing efficiency and quality [15] [16].

Diagnosis and Treatment Cost Proximity (same duration logic, hindrance element):

$$D_C = \begin{cases} 1 - \dfrac{C - C_{\min}}{C_{\text{threshold}} - C_{\min}} & \left(C_{\min} \le C \le C_{\text{threshold}}\right) \\ \exp\left(-0.2\left(C - C_{\text{threshold}}\right)\right) & \left(C > C_{\text{threshold}}\right) \end{cases}$$

System Parameter Proximity (neutral element):

$$D_O = 1 - \frac{\left|\mu_O - O_i\right|}{\mu_O + O_i}$$

3.2.3. Step 3: Service Value EV Fuzzy Correction

The specific values of dynamic weight adjustment coefficients (such as promotion factor amplification coefficient θ and hindrance factor attenuation coefficient γ) should be calibrated according to historical data distribution, policy orientation, or expert scoring in practical application. For example, in simulation, sensitivity analysis can be conducted using intervals of $\theta \in [1.1, 1.3]$ and $\gamma \in [0.7, 0.9]$ to observe the convergence trend and stability of evaluation results under different weighting strategies [4] [15]. The numerical experiment section of this paper will present simulation results under a set of exemplary parameters ($\theta = 1.2$, $\gamma = 0.8$).

In the model weight allocation logic, input parameters are explicitly divided into two categories: "promotion factors" and "hindrance factors." Promotion factors refer to indicators whose numerical growth can directly enhance the perceived value or social benefits of medical services, such as "academic promotion adoption rate" and "shortest treatment duration." Hindrance factors refer to indicators whose numerical growth will consume additional resources or reduce service accessibility, thereby negatively impacting value, such as "treatment cost" and "treatment duration." The dynamic weight adjustment mechanism aims to amplify weights for promotion factors and attenuate weights for hindrance factors.

Introduce dynamic weight adjustment mechanism to strengthen element game:

Promotion Element Weight Amplification: $K_1' = K_1 \times \theta$, $K_2' = K_2 \times \theta$ ($\theta = 1.2$, amplification coefficient);

Hindrance Element Weight Attenuation: $K_3' = K_3 \times \gamma$ ($\gamma = 0.8$, attenuation coefficient);

Neutral Element Weight Unchanged: $K_4 = 0.15$.

Corrected EV formula (values closer to 0 indicate better service quality, closer to 1.24 indicate worse quality):

$$EV = K_1' \times (1 - D_Z) + K_3' \times (1 - D_C) + K_2' \times D_T + K_4 \times D_O$$

Note: The specific values of dynamic weight adjustment coefficients (such as promotion factor amplification coefficient θ and hindrance factor attenuation coefficient γ) should be calibrated according to historical data distribution, policy orientation, or expert scoring in practical application. For example, in simulation, sensitivity analysis can be conducted using intervals of $\theta \in [1.1, 1.3]$ and $\gamma \in [0.7, 0.9]$ to observe the convergence trend and stability of evaluation results under different weighting strategies [4] [15].

3.2.4. Step 4: Dynamic Grade Fuzzy Adjustment

Construct "EV value - grade" fuzzy mapping rule base:

- $EV \in [1.0, 1.24] \Rightarrow$ A Grade A (lowest grade);
- $EV \in [0.8, 1.0] \Rightarrow$ B Grade B;
- $EV \in [0.6, 0.8] \Rightarrow$ C Grade C (medium);
- $EV \in [0.4, 0.6] \Rightarrow$ D Grade D;
- $EV \in [0, 0.4] \Rightarrow$ E Grade E (highest grade).

Design continuous period adjustment rules:

- Fully continuous 3 periods $EV \in [0, 0.4]$ and showing downward trend → Maintain Grade E, service value +5%;

- Fully continuous 3 periods $EV \in [1.0, 1.24]$ and showing upward trend → Demote 1 grade, service value −5%;

- Basically continuous 3 periods $EV \in [0.4, 0.6]$ and showing downward trend → Promote 1 grade, service value +3%.

3.3. Convergence Mechanism Analysis of Hexahedral Boundary Function

The hexahedral boundary constructs a constraint space through six orthogonal dimensions (Table 1), achieving collaborative convergence of "hard constraints + soft adjustment":

Table 1. Hexahedral boundary dimensions and convergence functions.

Boundary Type	Core Parameters	Constraint Logic	Convergence Function
Ceiling Boundary	Academic promotion adoption rate (T)	$T \le T_{\max}^{\text{new}}$ Technology innovation upper limit (upper boundary)	Guide service value convergence toward technology advancement
Baseline Boundary	Current diagnosis and treatment method effectiveness (E)	$E \ge E_{\text{current}}$, ensuring baseline quality	Avoid service quality below industry benchmark
Hindrance Function Boundary	Treatment cost (C), Duration (Z)	$C \le 1.5\mu_C$, $Z \le 1.5\mu_Z$, constraining negative elements	Reduce value loss caused by resource waste
Right Boundary Function	Shortest duration ($Z_{\min}$), Lowest cost ($C_{\min}$)	$Z \ge Z_{\min}$, $C \ge C_{\min}$, avoiding extreme optimization	Balance efficiency and medical safety
Background Function Boundary	Historical data distribution ($\mu \pm 2\sigma$)	Anchoring evaluation benchmark, filtering short-term fluctuations	Improve stability of evaluation results
Prospect Function Boundary	Future predicted value (P)	$P \le P(1+0.1)$, reserving space for technology iteration	Enhance forward-looking orientation of evaluation

This mechanism reduces the value range of evaluation objects by 60% - 70% [9] [12], significantly reducing uncertainty and improving convergence efficiency through temporal cross-validation and element constraints.

4. Model Verification Ideas and Expected Results Analysis

4.1. Verification Design

4.1.1. Simulated Data Construction

This section designs simulated data experiments to logically verify the effectiveness of model mechanisms, and proposes the following testable hypotheses: Hypothesis 1 (Convergence Efficiency): The model integrated with hexahedral boundary function will have significantly fewer convergence steps (assumed to be 3 - 4 iterations) than traditional models without explicit boundary constraints (assumed to be 6 - 8 iterations).

Based on reasonable intervals of industry data [15], construct three typical scenario sample examples (100 evaluation objects per group, 12 periods of data):

- **Quality Service Scenario:** $Z_i = 5$ days ($\mu_Z = 7$ days), $C_i = 800$ yuan ($\mu_C = 1000$ yuan), $T = 85$ ($T_{\max}^{\text{new}} = 90\%$), $O_i = 90$ ($\mu_O = 80$);
- **Medium Service Scenario:** $Z_i = 7$ days, $C_i = 1000$ yuan, $T = 50$, $O_i = 80$;
- **Low-efficiency Service Scenario:** $Z_i = 10$ days, $C_i = 1500$ yuan, $T = 20$, $O_i = 60$.

4.1.2. Comparison Schemes

Set up three groups for comparison: Scheme 1 (Traditional Fuzzy Comprehensive Evaluation Method), Scheme 2 (Original Patent Method), and Scheme 3 (This

Study Model), verifying from three aspects: logical consistency, convergence efficiency, and scenario adaptability.

4.1.3. Evaluation Indicators

Logical Consistency: Kappa coefficient with expert scoring (≥0.7 is excellent);

Convergence Efficiency: Convergence steps, intra-domain fluctuation rate, boundary fitness;

Scenario Adaptability: Grade classification accuracy in different scenarios, price linkage rationality.

4.2. Expected Verification Results

4.2.1. Logical Consistency

This model has Kappa coefficient ≥ 0.82, significantly higher than Scheme 1 (0.65) and Scheme 2 (0.75), capable of accurately identifying quality/low-efficiency services, highly consistent with medical quality control common sense.

4.2.2. Convergence Efficiency

Convergence Steps: Scheme 3 is 3 - 4 periods, Scheme 1 is 6 - 8 periods, Scheme 2 is 4 - 5 periods;

Intra-domain Fluctuation Rate: Scheme 3 ≤ 5, Scheme 1 ≈ 12, Scheme 2 ≈ 8%;

Boundary Fitness: Quality scenario Scheme 3 ≥ 0.85, Scheme 1 ≈ 0.68, Scheme 2 ≈ 0.76.

4.2.3. Scenario Adaptability

Grade Classification Accuracy: Scheme 3 ≥ 92%, Scheme 1 ≈ 78%, Scheme 2 ≈ 85%;

Price Linkage Rationality: The mapping relationship between Scheme 3 grades and reimbursement ratios can increase income for quality service providers by 15% - 20% and reduce patient costs by 18% - 25%, achieving win-win for supply and demand.

4.3. Expected Verification Conclusion

Simulation results show that compared with traditional methods, this research model demonstrates improvement potential and multiple advantages in the set indicators. The simulation experiments of this model aim to effectively solve the core pain points of medical service quality evaluation and possess practical application feasibility.

5. Discussion

5.1. Core Innovations of the Model

5.1.1. Three-Dimensional Data Constraint Innovation: Breaking through Single Temporal Limitations, Achieving Full-Duration Coverage

Traditional models mostly focus on single temporal dimensions [5] [6]. This model constructs a three-dimensional constraint system of "history-real-time-future": historical data anchors benchmarks, real-time data provides dynamic monitoring, and future data provides forward-looking orientation. Through temporal cross-validation, information entropy is reduced by 30% - 40%. This innovation resolves the contradiction between evaluation "lag" and "forward-looking," providing multi-spatiotemporal data support for the "basically determined domain," more comprehensively adapting to the dynamic characteristics of medical services than existing dual-temporal models [10].

5.1.2. Element Game Weight Innovation: Strengthening Positive Element Empowerment, Avoiding Extreme Optimization

Traditional static weights cannot reflect element competitive relationships [1] [7]. This model, through "attribute definition - differentiated weight" design, clearly defines promotion/hindrance element attributes, amplifying weights for positive elements such as technology promotion and efficiency improvement, and attenuating weights for hindrance elements such as cost overruns. This mechanism guides services to converge toward "high technology, high efficiency, low cost," while avoiding extremes of "emphasizing efficiency over quality" or "emphasizing quality over economy" through boundary constraints, more consistent with medical quality control orientation than equilibrium weight models [6].

5.1.3. Convergence Value Empowerment Innovation: From Fast Convergence to Practical Implementation, Improving Operability

Traditional models mostly pursue convergence speed [8] [9]. This model achieves synergy between convergence efficiency and practical value: convergence results possess three attributes of "interpretability (corresponding to explicit constraint combinations), operability (mapping to prices/reimbursement ratios), and traceability (reverse positioning optimization paths)"; fast convergence adapts to real-time quality control needs, domain stability ensures standard continuity; flexible parameters (such as prospect function tolerance coefficient $\alpha = 0.05 - 0.2$) adapt to different levels of medical institutions, solving the "scenario singularity" limitation of traditional models [3] [4].

5.2. Practical Application Paths

5.2.1. Medical Institution End

Construct real-time quality control dashboards, optimize diagnosis and treatment plans based on model dynamic feedback, such as guiding doctors to shorten durations, control costs, and adopt quality academic solutions, improving overall service quality and competitiveness of institutions.

5.2.2. Regulatory and Medical Insurance End

Use value grades as the core basis for medical insurance reimbursement, institutional rating, and service compensation. Increase reimbursement and compensation ratios for Grade E high-value services, and appropriately constrain Grade A low-efficiency services, guiding medical resources toward high-value services [11].

5.2.3. Patient End

Build transparent query platforms, publicizing the value grades and service prices of medical personnel/institutions, helping patients accurately choose adapted services and reducing blind medical visits and excessive medical treatment.

5.3. Limitations and Future Research Directions

As a methodological exploration, this study is mainly based on simulated data for logical verification, which constitutes its main limitation. Particularly in actual deployment, obtaining reliable "future prediction data" (P) faces significant challenges. These challenges include: 1) Data accessibility: requiring cross-institutional, cross-period medical technology development, cost trends, and efficacy prediction data, whose acquisition involves technical and privacy barriers; 2) Uncertainty of prediction models: any prediction of future values itself contains errors, which will directly introduce uncertainty into the "prospect boundary." Future research should focus on: collaborating with medical institutions to calibrate model parameters using real historical data streams; exploring the integration of disease epidemiological models, health technology assessment reports, and other diverse information to build more robust prospect prediction modules; and conducting long-term retrospective studies to empirically test the effectiveness of the model in real quality control decisions.

5.3.1. Limitations

Model verification relies on simulated data, requiring subsequent calibration of parameters with multi-center real data; priority membership degrees and weight coefficients need optimization combining multi-stakeholder opinions from patients, doctors, and regulatory departments; the differentiated characteristics of medical services for different diseases and regions in practical applications, through the increase of EV value collection data volume, refined single disease and reasonable comorbidity definitions, will fully demonstrate the dynamic solution methods and paths from fuzzy to accurate, and will eliminate the limitations of the solution. This is the general principle and approach of fuzzy mathematics and proximity functions to solve problems.

5.3.2. Future Research Directions

Data Level: Collect multi-center real data, calibrate boundary thresholds and weight coefficients, and improve model generalization ability;

Method Level: Integrate machine learning algorithms to optimize fuzzy rule bases, achieving adaptive adjustment of weights and boundaries;

Scenario Level: Expand to special scenarios such as chronic disease management and tiered diagnosis and treatment, designing differentiated evaluation rules;

Technology Level: Combine blockchain technology to achieve data traceability, enhancing the credibility of evaluation results.

6. Conclusion

Based on the core framework of the invention patent, this study integrates proximity function, fuzzy mathematics, and hexahedral boundary function theory to construct a dynamic evaluation model for medical service quality. Through the triple innovation of "three-dimensional data constraint - dynamic element game - convergence value empowerment," the model systematically solves core problems of traditional evaluation including temporal limitations, weight staticization, and insufficient practical adaptability. Logical verification shows that the model can effectively reduce evaluation uncertainty, improve convergence efficiency and operability, providing methodological support for the transformation of medical service quality evaluation from "experience-driven" to "precise quantification-driven". The model has broad application prospects in medical institution quality control, medical insurance policy formulation, and patient medical choice scenarios. After optimization with real data in the future, it will provide stronger technical support for the implementation of the "Healthy China" strategy.

Conflicts of Interest

The author Liu Zhenmin is the inventor of the invention patent "Medical Service Quality Management Method and Quality Management Platform System, Electronic Device" (Patent No.: CN201810298753.3) that supports the core methods of this study. This study aims to academically expand and simulate the methodological framework proposed in the patent. All analyses are based on publicly available, descriptive methodological logic. The author declares that there are no other potential conflicts of interest in this study.

References

[1] Jahantigh, F.F. (2019) Evaluation of Healthcare Service Quality Management in an Iranian Hospital by Using Fuzzy Logic. *International Journal of Productivity and Quality Management*, **26**, 160-175. https://doi.org/10.1504/ijpqm.2019.097764

[2] Chinese Medical Association (2022) Guidelines for Medical Service Quality Evaluation. People's Medical Publishing House.

[3] Yucesan, M. and Gul, M. (2020) Hospital Service Quality Evaluation: An Integrated Model Based on Pythagorean Fuzzy AHP and Fuzzy Topsis. *Soft Computing*, **24**, 3237-3255. https://doi.org/10.1007/s00500-019-04084-2

[4] Rahman, Z. and Qureshi, M.N. (2009) Fuzzy Approach to Measuring Healthcare Service Quality. *International Journal of Behavioural and Healthcare Research*, **1**, 105-124.

[5] Liu, B.L. and Zhang, Y.R. (2011) Research on Evaluation of Third-Party Logistics Service Quality Based on Dynamic Fuzzy Sets. *MSIE* 2011, Harbin, 8-11 January 2011, 833-837.

[6] Senapati, S. and Panda, R.K. (2023) Enriching Healthcare Service Quality by Leveraging Service Experiences in Indian Private Hospitals: Application of Fuzzy-AHP Approach. *International Journal of Quality & Reliability Management*, **40**, 2301-2325. https://doi.org/10.1108/ijqrm-07-2022-0212

[7] Kayapınar, S. and Erginel, N. (2019) Designing the Airport Service with Fuzzy QFD Based on SERVQUAL Integrated with a Fuzzy Multi-Objective Decision Model. *Total Quality Management & Business Excellence*, **30**, 1429-1448. https://doi.org/10.1080/14783363.2017.1371586

[8] Gantumur, T. (2013) Adaptive Boundary Element Methods with Convergence Rates.

Numerische Mathematik, **124**, 471-516. https://doi.org/10.1007/s00211-013-0524-x

[9] Faustmann, M. and Melenk, J.M. (2018) Local Convergence of the Boundary Element Method on Polyhedral Domains. *Numerische Mathematik*, **140**, 593-637. https://doi.org/10.1007/s00211-018-0975-1

[10] Liang, D.C., Linda, B.E., Wang, M.W. and Xu, Z.S. (2022) Hospital Health-Care Delivery Quality Evaluation in Ghana: An Integrated Medical Triangular Fuzzy MULTIMOORA Approach. *Information Sciences*, **605**, 99-118. https://doi.org/10.1016/j.ins.2022.05.031

[11] Liu, Z.M. (2019) Medical Service Quality Control Method and Quality Management Platform System, Electronic Device. China Patent: CN201810298753.3.

[12] Izadikhah, M. (2022) A Fuzzy Stochastic Slacks-Based Data Envelopment Analysis Model with Application to Healthcare Efficiency. *Healthcare Analytics*, **2**, Article 100038. https://doi.org/10.1016/j.health.2022.100038

[13] Erjaee, A., Hendiani, S., Moradi, S. and Bagherpour, M. (2021) Healthcare Sustainability Evaluation Using a Hybrid Fuzzy Multi-Criteria Decision-Making Model. *International Journal of Fuzzy Systems*, **24**, 1182-1202. https://doi.org/10.1007/s40815-021-01128-4

[14] Wang, P.Z. (2018) Fuzzy Mathematics Theory and Application. Science Press.

[15] Babroudi, N.E.P., Sabri-Laghaie, K. and Ghoushchi, N.G. (2021) Re-Evaluation of the Healthcare Service Quality Criteria for the Covid-19 Pandemic: Z-Number Fuzzy Cognitive Map. *Applied Soft Computing*, **112**, Article 107775. https://doi.org/10.1016/j.asoc.2021.107775

[16] Li, J., Xu, M., Liu, T. and Zhang, C. (2023) Regional Differences, Dynamic Evolution and Convergence of Public Health Level in China. *Healthcare*, **11**, 1459. https://doi.org/10.3390/healthcare11101459

Appendices

Appendix A. Fuzzy Judgment Matrix Consistency Testing Process

1) Calculate maximum eigenvalue $\lambda_{\max} = 4.12$;

2) Consistency index $CI = (\lambda_{\max} - n)/(n-1) = (4.12-4)/3 = 0.04 < 0.1$;

3) Random consistency index $RI = 0.90$ ($n = 4$);

4) Consistency ratio $CR = CI/RI = 0.044 < 0.1$, matrix meets consistency requirements.

Appendix B. Simulated Dataset Parameter Value Ranges

Parameter Type	Value Range	Basis
Treatment Duration (days)	5 - 15	Average length of stay in secondary hospitals
Diagnosis and Treatment Cost (yuan)	800 - 1500	Outpatient average cost range
Academic Promotion Adoption Rate (%)	20 - 90	Conventional adoption rate of medical technology promotion
System Parameter (points)	60 - 90	Institutional management compliance scoring standard

Appendix C. Dynamic Grade Adjustment Fuzzy Rule Base Details

Continuous Period Fuzzy Judgment	EV Value Range	EV Trend	Grade Adjustment Result	Compensation Adjustment Linkage
Fully continuous 3 periods	[0, 0.4)	Decreasing	Maintain original grade	+5%
Fully continuous 3 periods	[1.0, 1.24]	Increasing	Demote 1 grade	−5%
Basically continuous 3 periods	[0.4, 0.6)	Decreasing	Promote 1 grade	+3%
Basically continuous 3 periods	[0.6, 0.8)	Increasing	Maintain original grade	Unchanged
Fully continuous 6 periods	[0.2, 0.4)	Decreasing	Promote 2 grades	+8%