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The impact of healthcare delivery configuration on patients' perceived service quality: Mediating roles of patient partnership and trust in Nanning, China

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Abstract: In the evolving landscape of modern healthcare, the mere provision of medical resources is insufficient to guarantee patient satisfaction. Understanding the internal mechanisms that translate structural configurations into perceived quality is crucial for hospital management. This study explores the impact of Healthcare Delivery Configuration (HDC) on Perceived Service Quality (SQ) within the medical context of Nanning, China. Based on the Stimulus-Organism-Response (SOR) theory and the SERVQUAL model, this research proposed a dual-pathway mediation framework. Data were collected from patients in various healthcare institutions, and structural equation modeling (SEM) combined with the bootstrap resampling method was employed to test the hypotheses and mediating effects. The empirical results indicate that HDC has a significant direct positive impact on SQ (beta = 0.525, $p < 0.001$). Furthermore, the mediation analysis confirms that Patient Partnership (PP) and Patient Trust (PT) play significant partial mediating roles. The indirect effect through the trust pathway was estimated at 0.131 (95% CI: [0.074, 0.198]), while the combined mediating pathways account for approximately 45% of the total effect (0.656). The findings suggest that while technical and structural optimizations are fundamental, their impact on service quality is significantly amplified when they foster collaborative doctor-patient partnerships and strengthen emotional trust. Healthcare providers should not only focus on physical resource allocation but also prioritize building communication platforms that empower patients and consolidate trust to maximize perceived service quality in resource-constrained environments.

Keywords: *Healthcare delivery configuration, Mediation analysis, Patient partnership, Patient Trust, Patients' perceived service quality, SOR theory.*

1. Background

Against the backdrop of changing demographic structures, constraints on medical resources, and rapid technological development, global healthcare systems are undergoing profound adjustments. The acceleration of population aging and the increase in the prevalence of chronic diseases have prompted healthcare service models to gradually shift from treatment-centered to comprehensive models that emphasize whole-process continuity, efficiency improvement, and patient experience [1, 2]. Within this trend, patients' perceived service quality has gradually become an important basis for measuring the

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effectiveness of healthcare systems; this indicator covers clinical treatment outcomes while also focusing on patients' overall feelings and subjective experiences throughout the entire medical seeking process.

Unlike objective technical indicators, patients' perceptions of service quality primarily stem from their overall evaluations of aspects such as doctor-patient communication, service responsiveness, degree of respect, and emotional care [3]. Existing research shows that perceived service quality plays an important role in patients' trust in medical institutions, adherence to treatment plans, satisfaction, and the long-term performance of medical institutions [4]. As medical services become increasingly regulated and standardized, patients' judgments of service quality place greater emphasis on whether the service process is transparent, whether there is humanistic care, and whether patients can truly participate in the diagnosis and treatment process.

The widespread use of digital technology is changing the way medical services are provided. Globally, auxiliary diagnosis, clinical decision support systems, and intelligent scheduling systems, while improving efficiency and accuracy, have also significantly affected patients' medical seeking experiences [5, 6]. Relevant experience indicates that technology itself does not necessarily improve patients' evaluations of service quality; its effect depends largely on how it is integrated into the service process and on how medical institutions explain the value and role of technology to patients [7, 8].

In China, the integration of artificial intelligence and medical services has received high-level national attention. From the "New Generation Artificial Intelligence Development Plan" to the continuous advancement of the "Internet + Medical Health" policy system, digitalization and intelligence have become important directions for transforming medical services [9, 10]. While these policies improve resource allocation efficiency and service standardization, they also introduce new challenges, such as patients' understanding of diagnostic and treatment logic, perceptions of responsibility attribution, and trust issues related to technological interventions in medical care [11, 12].

As the capital of Guangxi Zhuang Autonomous Region, Nanning City gathers the region's major Grade A tertiary hospitals and medical centers and is a leading force in smart medicine, internet hospitals, and AI-assisted diagnosis and treatment. However, unbalanced urban-rural development, complex population structures, and the growth of cross-regional medical-seeking demand have led to significant differences in patients' perceptions of service experiences during the actual medical-seeking process [13]. In this context, patients' evaluation of medical service quality is closely related to doctor-patient communication experience, institutional trust, and sense of participation.

Healthcare delivery configuration, as the overall arrangement of medical service processes, division of roles, and technology embedding methods, is an important foundation for shaping the patient's medical seeking experience. Cadario et al. [14] noted that simply optimizing service configuration does not necessarily improve patients' subjective evaluations; highly procedural or technology-oriented service arrangements may be perceived by some patients as failing to address individual needs. When patients find it difficult to understand service design logic or lack a sense of participation, changes in service models may instead weaken their overall perception of service quality.

Patient partnership and patient trust have become key mechanisms connecting healthcare delivery configuration and perceived service quality. Patient partnership emphasizes collaborative interaction, shared decision-making, and shared responsibility between doctors and patients, thereby enhancing patient engagement and service identification [15]. Patient trust reflects the patient's comprehensive judgment of the medical provider's professional ability, sense of responsibility, and benevolence, and is an important psychological foundation for their acceptance of new service models and technological interventions [16].

From the perspective of medical service resource allocation, systematic analyses of the mediating role of patient participation and patient trust are still relatively limited at present, especially empirical studies that combine specific cases in Chinese cities need to be further strengthened. Based on the realistic background of medical development in Nanning, this paper intends to explore how healthcare delivery configuration promotes patient participation and enhances patient trust, thereby improving patients' perceived service quality, with a view to providing a new empirical reference for understanding the connection between institutional optimization and patient experience during the transformation of China's medical services.

2. Theoretical Foundation and Hypothetical Construct

Patients' evaluation of medical service quality is no longer solely based on objective clinical outcomes but is gradually shifting towards a comprehensive assessment of service processes, interaction experiences, and psychological feelings [17]. Therefore, it is necessary to introduce an integrated theoretical framework that can simultaneously explain institutional arrangements, psychological mechanisms, and outcome evaluations. Based on this, this study adopts the Stimulus-Organism-Response (SOR) theory as the overall analytical logic and utilizes the SERVQUAL model as the specific measurement and explanatory tool for perceived service quality to construct a theoretical model of how healthcare delivery configuration affects patients' perceived service quality.

Under the SOR theoretical framework [18] healthcare delivery configuration is regarded as the external stimulus, including institutional and contextual arrangements such as the dominant mode of medical service, the degree of technology embedding, service process structure, and doctor-patient interaction patterns. These stimuli do not directly determine the patient's final evaluation; rather, they first act upon the patient's internal psychological and behavioral state, namely the "Organism." In the medical context, the patient's internal response is mainly reflected at two levels: first, the patient partnership, centered on shared decision-making, joint planning, and problem-solving; second, the patient trust structure, composed of cognitive and affective trust. Ultimately, these psychological and behavioral changes jointly shape the patient's overall perception and evaluation of medical service quality, which is the response.

From the perspective of direct effects, different healthcare delivery configurations can directly alter patients' judgments of the reliability, safety, and professionalism of medical services by affecting service efficiency, information transparency, and responsibility allocation [19]. Therefore, the healthcare delivery configuration itself should significantly impact patients' perceived service quality.

H1: Healthcare delivery configuration has a significant positive impact on patients' perceived service quality.

Optimizing healthcare delivery configuration does not necessarily translate into patients' subjective recognition. Its effect depends largely on the patient's experience of participation and psychological identification during the service process [20]. In this sense, patient partnership serves as an important mediating mechanism linking institutional arrangements and subjective evaluations. When patients participate in decision-making, understand the logic of diagnosis and treatment, and form collaborative relationships with medical personnel during the clinical process, their sense of control and responsibility regarding medical services is significantly enhanced, making it easier to provide positive service evaluations [21].

H2: Healthcare delivery configuration has a significant positive impact on patient partnership.

H3: Patient partnership has a significant positive impact on patients' perceived service quality.

H4: Patient partnership mediates between healthcare delivery configuration and patients' perceived service quality.

At the same time, patient trust is an indispensable psychological foundation in the healthcare service context. The degree of technology embedding, process standardization, and service-dominant logic directly affects patients' judgments of the medical system's professional competence, ethical boundaries, and benevolent motives [22]. A reasonable healthcare delivery configuration helps enhance patients' cognitive and affective trust in medical institutions and personnel, while greater trust can significantly improve patients' overall perception of service safety, stability, and humanistic care [23].

H5: Healthcare delivery configuration has a significant positive impact on patient trust.

H6: Patient trust has a significant positive impact on patients' perceived service quality.

H7: Patient trust mediates the relationship between healthcare delivery configuration and patients' perceived service quality.

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On this basis, this study introduces the SERVQUAL model into the response level to systematically characterize the multidimensional structure of patients' perceived service quality [24]. The reliability, responsiveness, assurance, empathy, and tangibles emphasized by SERVQUAL can reflect patients' rational judgments of service outcomes while also capturing their emotional experiences during medical interactions [17]. By combining SERVQUAL with the SOR framework, this paper constructs a comprehensive model capable of simultaneously explaining institutional stimuli, psychological mechanisms, and perceived outcomes, thereby providing a systematic explanation for the formation mechanism of patients' perceived service quality against the background of smart healthcare transformation in Nanning.

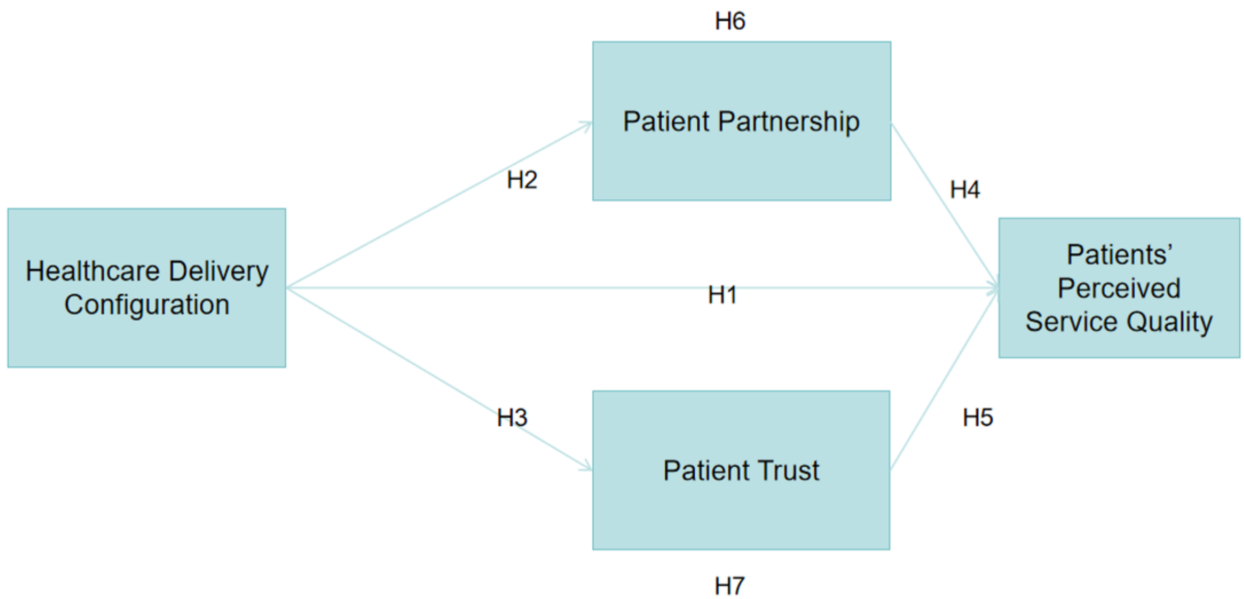

Figure 1.
Conceptual Framework.

3. Methodology

3.1. Research design

Gion, China. As a regional medical center, Nanning is highly representative in the construction of smart healthcare, the promotion of medical consortia, and the application of artificial intelligence-assisted diagnosis and treatment. The data mainly come from the outpatient areas of four tertiary hospitals in Nanning City, ensuring that the samples cover diverse medical scenarios and patient groups. The research subjects are patients who have received actual medical services in Nanning City within the past year. Data collection was conducted by combining on-site intercepts with online questionnaires. Survey points were set up in the hospital's outpatient department waiting area, guiding patients to complete online questionnaires via QR codes. Technical screening was conducted through the questionnaire system for the duration of filling, logical consistency, and repeated submissions. A total of 465 valid questionnaires were ultimately collected for subsequent statistical analysis.

3.2. Research Instrument

This study adopts structured questionnaires as the main research tool. The questionnaire consists of three parts: guiding instructions, demographic information, and core measurement scales. All scales use the 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The Healthcare Delivery Configuration scale is a self-developed and adapted scale that measures patients' overall perception of the current medical service model, covering dimensions of intelligent service processes, technology-assisted decision-making, and traditional doctor-centered, humanistic interaction. Patient Partnership primarily refers to the research framework of Carman [25] regarding patient engagement and shared decision-making, focusing on measuring the degree of patients' information participation, decision-making participation, and cooperation during the clinical process. The Patient Trust scale is adapted from Doney and Cannon [26] and assesses the level of patient trust in medical service entities (doctors and systems) across two dimensions: cognitive trust and affective trust. Perceived Service Quality is based on the SERVQUAL model proposed by Parasuraman et al. [24] with appropriate adjustments for the medical context, encompassing core dimensions such as reliability, responsiveness, assurance, and empathy.

3.3. Data Analysis

Data analysis was completed in two stages. First, descriptive statistical analysis, Cronbach's α reliability test, and exploratory factor analysis (EFA) were conducted using SPSS to examine the scale's internal consistency and potential structure. Second, AMOS software was used to conduct confirmatory factor analysis (CFA) and structural equation modeling (SEM), systematically testing the measurement and structural models to verify the research hypotheses and the path relationships among the variables.

4. Results

4.1. Descriptive Statistics Analysis

Among all measurement indicators for Healthcare Delivery Configuration (HDC), Patient Partnership (PP), Patient Trust (PT), and Perceived Service Quality (SQ), the mean values fluctuate around the median of 3.00 on a 5-point Likert scale, ranging from 2.94 to 3.07. The mean scores for Healthcare Delivery Configuration range from 2.94 to 3.02, reflecting that patients in Nanning perceive the current integration of intelligent processes and traditional humanistic interaction to be at a moderate stage of development. Patient Partnership and Patient Trust exhibit a similar pattern, among which PT7 (Mean = 3.07, SD = 1.129) and PP2 (Mean = 3.06, SD = 1.132) score slightly higher, indicating that respondents are in a relatively stable state, with room for improvement in collaborative engagement and institutional trust. For Patients' Perceived Service Quality, the mean values (2.95 to 3.05) embody patients' balanced evaluation of service reliability and empathy. From the perspective of distributional characteristics, the absolute values of skewness and kurtosis for all items are far below 2, indicating that the data approximates a normal distribution. This normality provides a rationale for subsequently using covariance-based structural equation modeling or regression-based path analysis to verify the moderated mediation framework proposed in this study. In addition, the standard deviations mostly remain between 0.995 and 1.162, proving that patients' responses possess sufficient variability.

Table 1.
Descriptive Statistics.

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
HDC1	465	1	5	2.94	1.111	0.035	-0.553
HDC2	465	1	5	3.02	1.085	0.028	-0.477
HDC3	465	1	5	2.95	1.068	-0.025	-0.413
HDC4	465	1	5	3.00	1.075	-0.054	-0.455
HDC5	465	1	5	3.02	1.124	0.058	-0.579
HDC6	465	1	5	2.98	1.089	-0.003	-0.439
HDC7	465	1	5	2.96	1.121	0.012	-0.544
HDC8	465	1	5	2.96	0.995	0.025	0.032
PP1	465	1	5	2.94	1.024	0.085	-0.166
PP2	465	1	5	3.06	1.132	-0.002	-0.662
PP3	465	1	5	2.99	1.110	0.017	-0.611
PP4	465	1	5	3.01	1.080	-0.052	-0.433
PP5	465	1	5	3.03	1.054	-0.127	-0.442
PP6	465	1	5	3.04	1.134	-0.027	-0.647
PP7	465	1	5	3.01	1.161	-0.063	-0.691
PP8	465	1	5	2.98	1.095	-0.031	-0.560
PT1	465	1	5	3.01	1.035	0.022	-0.316
PT2	465	1	5	2.97	1.130	0.028	-0.541
PT3	465	1	5	3.00	1.109	0.034	-0.501
PT4	465	1	5	2.98	1.139	-0.054	-0.624
PT5	465	1	5	3.00	1.076	-0.048	-0.404
PT6	465	1	5	3.03	1.125	0.022	-0.591
PT7	465	1	5	3.07	1.129	-0.077	-0.577
SQ1	465	1	5	3.04	1.162	0.020	-0.595
SQ2	465	1	5	2.95	1.108	-0.006	-0.538
SQ3	465	1	5	3.05	1.159	0.024	-0.737
SQ4	465	1	5	2.97	1.130	0.127	-0.547
SQ5	465	1	5	2.98	1.120	-0.040	-0.616
Valid N (listwise)	465						

4.2. Reliability Analysis

In this study, Cronbach's alpha was computed for each research variable in SPSS, and the results indicate that the reliability coefficients for all dimensions exceed the recommended threshold of 0.7. The alpha coefficients for Healthcare Delivery Configuration (HDC) and Patient Partnership (PP) reached 0.903 and 0.906, respectively, demonstrating excellent internal consistency. The alpha coefficient for Patient Trust (PT) is 0.889, and the alpha coefficient for Perceived Service Quality (SQ) is 0.873. These reliability performances are equally outstanding, indicating that the scale items can stably reflect the characteristics of the latent variables.

Table 2.
Reliability Results.

Constructs	Cronbachα
HDC	0.903
PP	0.906
PT	0.889
SQ	0.873

4.3. Exploratory Factor Analysis (EFA)

Before conducting the formal factor analysis, this study evaluated the appropriateness of the data sampling and the correlation among variables using the KMO (Kaiser-Meyer-Olkin) test and Bartlett's test of sphericity. The results show that the KMO statistic is 0.947, well above the excellent threshold of 0.8. This indicates that there are very strong common features among the observed items, and the sample size is sufficient. The data are well-suited for factor analysis. Meanwhile, the approximate chi-square value for Bartlett's sphericity test was 6991.994, with a significance level of 378 degrees of freedom ($p < 0.001$). This indicates that the correlation matrix of the original variables is not an identity matrix, and there is significant correlation among the variables, which meets the statistical assumptions for conducting structural equation modeling.

Table 3.
KMO and Bartlett's Test.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.947
Bartlett's Test of Sphericity	Approx. Chi-Square	6991.994
	df	378
	Sig.	0.000

4.3.1. Total Variance Explained

According to the Total Variance Explained Table, four factors had eigenvalues greater than 1 before rotation, which closely aligns with the theoretical dimensions set in this study. These four principal components jointly explained 61.433% of the total variance of the original variables, exceeding the empirical standard of 60% in social science research, indicating that the extracted factors can well cover most of the information of the original measurement items. From the perspective of the distribution of variance contributions, the initial eigenvalue for the first principal component was 10.260, explaining 36.643% of the variance. It is noteworthy that the explanatory power of the first principal component before rotation did not exceed 40%, which, to some extent, suggests that there is no serious Common Method Bias in the data of this study; that is, there is no single factor explaining the vast majority of the variance.

After the Varimax rotation, the variance distribution was more balanced, with the variance contribution rates of the four rotated factors being 17.578%, 16.868%, 15.380%, and 11.607%, respectively. This balanced distribution indicates that, through the orthogonal rotation process, the structure of each factor has become clearer, enabling them to independently and explicitly represent the core concepts of healthcare delivery configuration, patient partnership, patient trust, and perceived service quality. In summary, the exploratory factor analysis results further confirm that the scale possesses good construct validity. The four extracted factors have a stable structure and strong explanatory power, providing solid empirical support for subsequent verification of path relationships and mediating effects.

Table 4.
Total Variance Explained.

Total Variance Explained									
	Initial Eigenvalues			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	10.260	36.643	36.643	10.260	36.643	36.643	4.922	17.578	17.578
2	3.214	11.480	48.123	3.214	11.480	48.123	4.723	16.868	34.446
3	2.080	7.427	55.550	2.080	7.427	55.550	4.306	15.380	49.826
4	1.647	5.882	61.433	1.647	5.882	61.433	3.250	11.607	61.433
5	0.709	2.533	63.965						
6	0.672	2.399	66.365						
7	0.642	2.292	68.657						
8	0.598	2.134	70.791						
9	0.588	2.099	72.890						
10	0.561	2.002	74.892						
11	0.551	1.969	76.861						
12	0.507	1.812	78.673						
13	0.472	1.685	80.358						
14	0.468	1.670	82.029						
15	0.446	1.593	83.622						
16	0.442	1.580	85.202						
17	0.424	1.513	86.715						
18	0.410	1.464	88.179						
19	0.403	1.441	89.620						
20	0.389	1.389	91.009						
21	0.374	1.336	92.344						
22	0.346	1.236	93.580						
23	0.335	1.195	94.776						
24	0.333	1.188	95.963						
25	0.317	1.131	97.094						
26	0.290	1.035	98.129						
27	0.280	1.001	99.129						
28	0.244	.871	100.000						

Note: Extraction Method: Principal Component Analysis.

4.3.2. Principal Component Analysis (PCA)

The study employed Principal Component Analysis (PCA) with Varimax rotation to classify the 28 measurement items. The results of the rotated component matrix indicate that all items achieved good convergence after five iterations, and each measurement item exhibited significantly high loadings (all greater than 0.60) on its preset theoretical dimension. Factor 1 accurately extracted the eight items of Patient Partnership (PP), with loading values ranging from 0.688 to 0.757. Factor 2 corresponds to Healthcare Delivery Configuration (HDC), with loadings ranging from 0.635 to 0.738. Factors 3 and 4 correspond to Patient Trust (PT) and Perceived Service Quality (SQ), respectively, with loadings ranging from 0.678 to 0.789 and from 0.717 to 0.755, respectively. This clear factor structure demonstrates that the scale possesses excellent construct validity, and each measurement item precisely represents its intended theoretical construct.

Simultaneously, the matrix further confirms that the measurement instruments in this study possess superior discriminant validity. The cross-loadings of each item on non-target factors remain low (typically below 0.30), effectively avoiding identification confusion among factors. The number of measurement items per latent variable shows a uniform loading distribution, providing robust explanatory power for the constructs. This rigorous factor structure is consistent with the initial logical framework constructed based on the SOR theory and the SERVQUAL model.

Table 5.
Rotated Component Matrix.

Rotated Component Matrix				
	Component			
	1	**2**	**3**	**4**
HDC1	0.254	**0.727**	0.136	0.054
HDC2	0.183	**0.688**	0.208	0.145
HDC3	0.205	**0.712**	0.137	0.118
HDC4	0.181	**0.723**	0.169	0.163
HDC5	0.211	**0.723**	0.158	0.212
HDC6	0.181	**0.738**	0.149	0.177
HDC7	0.194	**0.734**	0.101	0.219
HDC8	0.265	**0.635**	0.210	0.104
PP1	**0.688**	0.199	0.078	0.109
PP2	**0.729**	0.192	0.088	0.138
PP3	**0.757**	0.183	0.073	0.183
PP4	**0.703**	0.228	0.065	0.166
PP5	**0.729**	0.193	0.085	0.205
PP6	**0.742**	0.176	0.119	0.193
PP7	**0.719**	0.252	0.087	0.183
PP8	**0.738**	0.172	0.068	0.180
PT1	0.042	0.238	**0.678**	0.107
PT2	0.132	0.124	**0.767**	0.109
PT3	0.090	0.142	**0.749**	0.102
PT4	-0.004	0.141	**0.743**	0.163
PT5	0.077	0.177	**0.722**	0.198
PT6	0.171	0.120	**0.772**	0.046
PT7	0.066	0.102	**0.789**	0.106
SQ1	0.255	0.221	0.164	**0.740**
SQ2	0.225	0.236	0.130	**0.720**
SQ3	0.236	0.191	0.196	**0.742**
SQ4	0.247	0.142	0.158	**0.755**
SQ5	0.219	0.173	0.178	**0.717**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Note: a. Rotation converged in 5 iterations.

4.4. Structural Equation Model (SEM)
4.4.1. Measurement Model Analysis

The chi-square-to-degrees-of-freedom ratio for the measurement model is 1.388, which is well below the empirical standard of 3, indicating that the discrepancy between the model and the data is small. RMSEA is 0.029, significantly lower than the excellent critical value of 0.05, reflecting that the model has an excellent parsimonious fit. In terms of incremental fit indices, CFI is 0.980, TLI is 0.978, and IFI is 0.980, all of which are far higher than the standard line of 0.90. Additionally, GFI is 0.933, and AGFI is 0.920, both of which are at ideal levels. This measurement model has extremely high adaptability to observation data from medical services in Nanning. The standardized loadings of the measurement items corresponding to each latent variable (HDC, PP, PT, SQ) are balanced, generally between 0.67 and 0.78, and the correlation coefficients between variables (0.32 to 0.62) are within a reasonable range, providing a solid quality guarantee for subsequent path testing of the structural equation model and the analysis of moderated mediation effects.

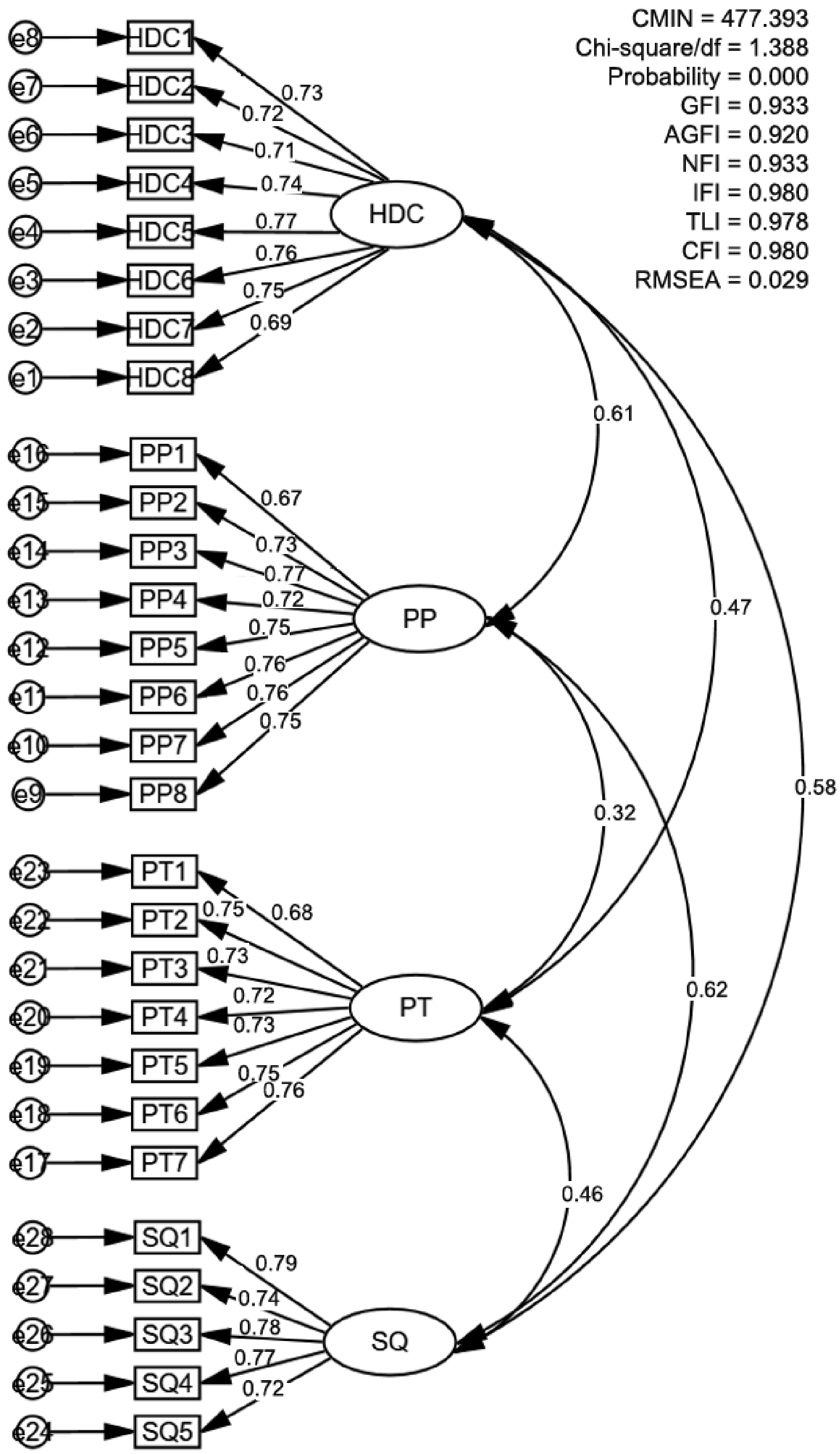

Figure 2.
Measurement Model.

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Table 6 presents the results of the scale's convergent validity and reliability tests. In terms of convergent validity, the average variance extracted (AVE) values for the four constructs range from 0.54 to 0.58, all exceeding the recommended threshold of 0.50, indicating that the latent variables explain more than half of the variance of their corresponding observed items. Meanwhile, all the standardized loadings are within the ideal range of 0.674 to 0.792, far above the threshold of 0.50, further confirming the good representativeness of the observed variables for the latent variables. In terms of reliability assessment, the composite reliability (CR) values range from 0.90 to 0.92, significantly higher than the criterion of 0.70. Combined with the previously reported Cronbach's alpha coefficients ranging from 0.847 to 0.906, the results collectively confirm that the measurement tool has extremely high internal consistency and reliability, laying a solid data quality foundation for subsequent model testing.

Table 6.
Results of Convergent Validity and Reliability Analysis.

Construct	Items	Standardized Factor Loading	AVE	CR
HDC	HDC1–HDC8	0.687–0.769	0.54	0.91
PP	PP1–PP8	0.674–0.771	0.55	0.92
PT	PT1–PT7	0.675–0.757	0.54	0.90
SQ	SQ1–SQ5	0.725–0.792	0.58	0.91

Table 7 employs the Fornell-Larcker criterion to test the discriminant validity among the constructs. According to the statistical requirements, the square root of the AVE of each construct should be greater than the correlation coefficients between it and other constructs. The bolded values on the diagonal of the table (0.73 to 0.76) represent the square roots of the AVEs of HDC, PP, PT, and SQ, respectively, which are significantly greater than the off-diagonal correlation coefficients in the same row and column (0.319 to 0.619). This result strongly indicates that the different latent variables are significantly discriminable, meaning that the traits measured by each construct are statistically independent and that there are no serious collinearity or overlap issues. The excellent discriminant validity ensures that this study accurately captures the independent contributions of each link when exploring how healthcare service configuration affects perceived service quality through patient partnership and trust, thereby enhancing the rigor of the research conclusions.

Table 7.
Discriminant Validity Analysis (Fornell-Larcker Criterion).

Construct	SQ	PT	PP	HDC
SQ	0.76			
PT	0.463	0.73		
PP	0.619	0.319	0.74	
HDC	0.578	0.475	0.607	0.73

4.4.2. Structural Model Analysis

The fit indices of the structural model demonstrate excellent performance and maintain high consistency with the measurement model (Figure 3). The chi-square to degrees of freedom ratio is 1.386, and the RMSEA is 0.029 (below 0.05). Furthermore, the CFI, TLI, and IFI are 0.980, 0.978, and 0.980, respectively (all exceeding 0.95). These indices indicate that the theoretical model developed in this study fits the survey data well and that the path analysis results exhibit very high statistical reliability.

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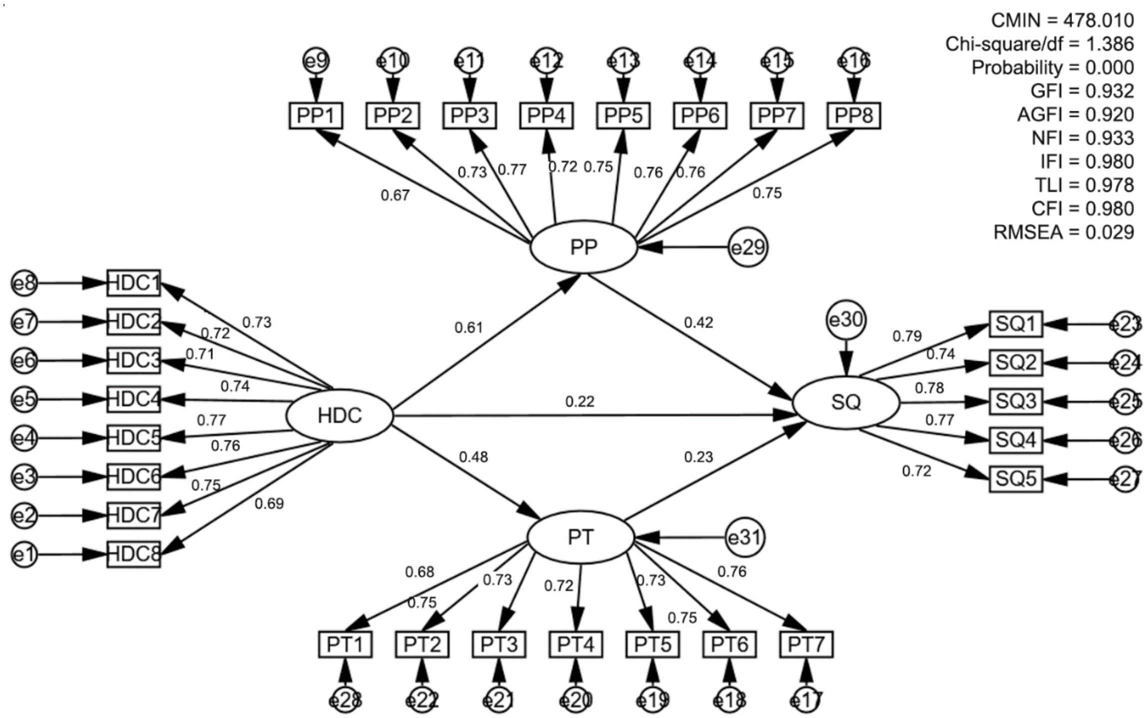

Figure 3.
Structural model.

Table 8.
Path Coefficients and Hypothesis Testing Results.

Hypothesis	Path	B	S.E.	C.R. (t-value)	P	Std. Est. (β)	Result
H1	HDC→SQ	0.246	0.069	3.591	***	0.218	Supported
H2	HDC→PP	0.516	0.050	10.298	***	0.609	Supported
H3	HDC→PT	0.410	0.049	8.429	***	0.477	Supported
H4	PP →SQ	0.552	0.079	6.969	***	0.415	Supported
H5	PT →SQ	0.301	0.065	4.593	***	0.229	Supported

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

4.4.3. Test of Mediating Relationship

As shown in Table 9, the Bootstrap resampling method was employed to test the mediating pathways through which Healthcare Delivery Configuration (HDC) affects Perceived Service Quality (SQ). The results indicate that the Total Effect coefficient is 0.653 (95% CI: [0.530, 0.776], $p < 0.001$), suggesting that enhancing healthcare delivery configuration significantly strengthens patients' overall perception of service quality. After incorporating mediating variables, the Direct Effect remains significant (beta = 0.362, $p < 0.001$), confirming HDC's direct role on SQ. A significant Indirect Effect was observed with a coefficient of 0.291, and its 95% confidence interval [0.210, 0.387] does not contain zero. This finding demonstrates that Patient Partnership (PP) and Patient Trust (PT) play a significant Partial Mediation role. Based on the structural model analysis, the indirect effect accounts for approximately 44.5% of the total effect (Figure 4), illustrating that healthcare delivery configuration can directly improve quality through technical and process optimization, while also enhancing perceived service quality by improving patient-provider collaboration (PP).

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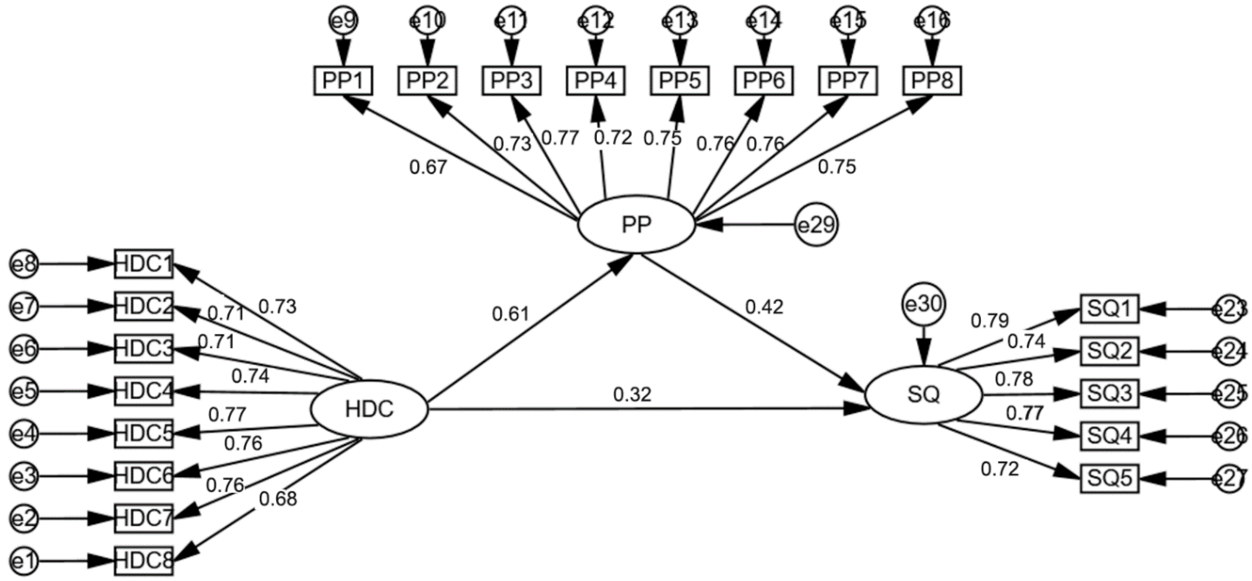

Figure 4.
Structural Equation Model of the Mediating Role of Patient Partnership.

Table 9.
Bootstrap Analysis of the Mediating Role of Patient Partnership.

Effect Type	Beta (β)	Lower 95% CI	Upper 95% CI	P-value
Direct Effect	0.362	0.233	0.500	0.001
Indirect Effect	0.291	0.210	0.387	0.001
Total Effect	0.653	0.530	0.776	0.001

As shown in Table 10, within the path model incorporating the mediating variable PT, the direct effect of HDC on SQ is significant, with a standardized path coefficient of 0.525 and a total effect value of 0.656. This indicates that optimizing healthcare delivery configuration is a core driver of improved service quality perception. Regarding the significance of the mediation effect, the estimated indirect effect of HDC on SQ through PT is 0.131. According to the bootstrap test results, the 95% confidence interval is [0.074, 0.198], which does not include zero and reaches the 0.001 significance threshold, confirming that patient trust plays a significant partial mediation role in the model. In terms of managerial implications, the data suggest that while technical configuration adjustments can directly improve patient evaluations, establishing and consolidating the emotional bond of patient trust can generate an additional gain of approximately 20% in perceived service quality, thereby enhancing healthcare service levels more comprehensively.

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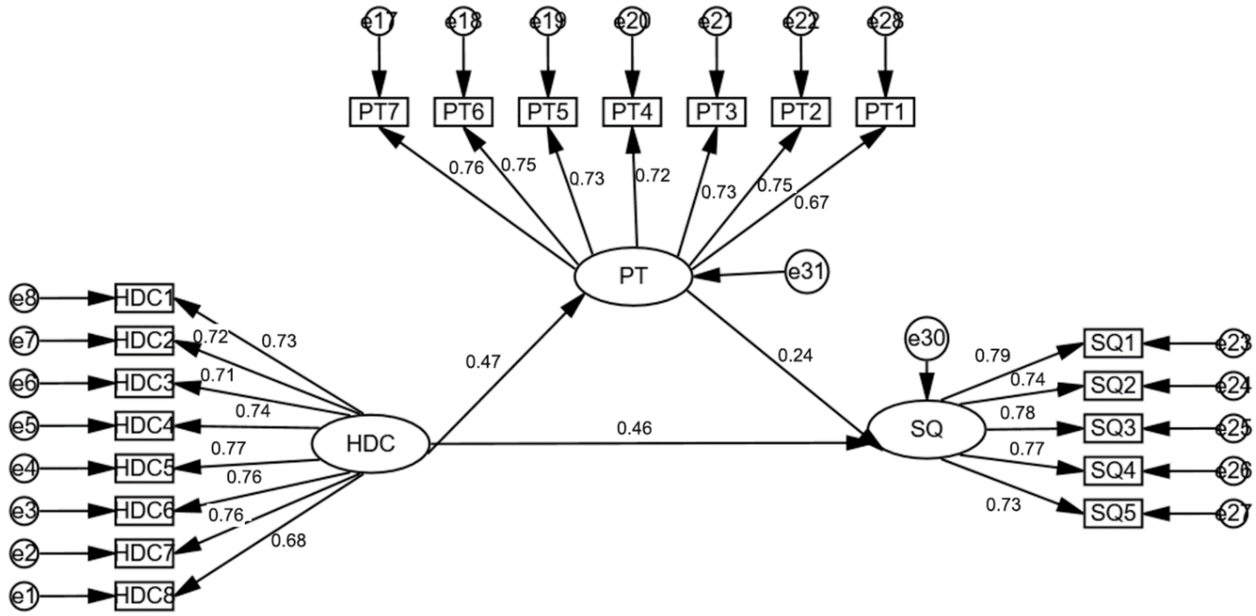

Figure 5.
Structural Equation Model of the Mediating Role of Patient Trust.

Table 10.
Bootstrap Analysis of Mediating Role of Patient Trust.

Effect Type	Beta (β)	Lower 95% CI	Upper 95% CI	P-value
Direct Effect	0.525	0.394	0.657	0.001
Indirect Effect	0.131	0.074	0.198	0.001
Total Effect	0.656	0.529	0.779	0.001

5. Discussion

This study explores the mechanism by which Healthcare Delivery Configuration (HDC) influences Patient Perceived Service Quality (SQ), and the results provide empirical support for all initial hypotheses. Structural model analysis indicates that HDC exerts a significant direct positive impact on SQ, suggesting that the scientific configuration of medical resources and the optimization of service processes serve as the essential foundation and prerequisite for enhancing patient satisfaction. Furthermore, bootstrap mediation testing reveals that Patient Partnership (PP) and Patient Trust (PT) each play a significant partial mediating role in this relationship, with these two pathways collectively explaining approximately 45% of the total effect. This indicates that optimizing healthcare configuration represents a technical improvement and, by fostering physician-patient collaboration and strengthening emotional trust, indirectly enhances the overall perception of service quality.

These results support the hypothesized theoretical model, demonstrating that superior healthcare structural configurations can be transformed into positive perceptual outcomes. From the perspective of the Stimulus-Organism-Response (S-O-R) theory, HDC serves as an external environmental stimulus, which acts upon the patient's psychological and emotional organism states (namely, Patient Partnership and Trust), ultimately eliciting the response of service quality evaluation. This aligns closely with the Structure-Process-Outcome (SPO) quality model proposed by Donabedian [27], confirming that resource investment at the "structure" level must be mediated through doctor-patient interaction at the "process" level to effectively translate into quality perception at the "outcome" level. Distinct from previous research that prioritized technical efficiency or rigid facility indicators, this study aligns with the modern patient-centered care philosophy by validating the mediating role of PP, demonstrating that when healthcare configurations facilitate active patient participation in treatment decisions, patients'

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quality perception improves significantly. Additionally, the mediating effect of PT reaffirms the critical importance of emotional connection for quality evaluation within the high-uncertainty environment of the healthcare industry.

The findings of this study are consistent with the classic discourse on healthcare quality assessment by Donabedian [27] and support the applicability of the S-O-R (Stimulus-Organism-Response) environmental psychology framework developed by Mehrabian and Russell [18] within healthcare service contexts. Similar to the dimensions of responsiveness and empathy emphasized by Parasuraman et al. [24] in the SERVQUAL model, this study identifies partnership and trust as the core linkages connecting physical configurations with perceived quality.

Regarding theoretical and practical contributions, this research unveils the pathway by which healthcare configuration is transformed into quality perception, constructing a dual-pathway mediation framework that encompasses both behavior (partnership) and emotion (trust), thereby providing a more comprehensive perspective on the patient experience. At the practical level, this study suggests that healthcare administrative departments should not only invest in hardware facilities but also prioritize optimizing configurations to build platforms for doctor-patient communication and collaboration, encouraging patients to actively participate in health management. Furthermore, given the additional gains from the trust pathway, hospitals should strengthen transparency of information and medical communication training to consolidate the foundation of patient trust, thereby maximizing perceived service quality within the constraints of limited resources.

6. Conclusion

This study systematically investigates the mechanism through which Healthcare Delivery Configuration (HDC) influences Patient Perceived Service Quality (SQ), providing empirical evidence for understanding the central role of doctor-patient relationships in healthcare quality management. The findings indicate that healthcare resource configuration can directly drive improvements in perceived service quality and also function through a dual-pathway mediation mechanism involving Patient Partnership (PP) and Patient Trust (PT). This discovery emphasizes that, in the modern healthcare environment, optimization at the technical and structural levels can only maximize perceived service quality when it is successfully translated into patients' psychological sense of gain and collaborative momentum between doctors and patients. By integrating the SOR theory and the SERVQUAL model, this research reveals that healthcare service is not merely a simple combination of resources but a complex cognitive process shaped by both behavioral engagement and emotional connection.

This research still has certain limitations in terms of breadth and depth and needs to be further improved in future research. Firstly, the samples were mainly concentrated in medical institutions in Nanning City. The geographical singularity might have restricted the promotion of the research results to regions with different levels of economic development or significant cultural background differences. Future research should expand the sample to enhance the generalizability of the conclusions. Secondly, this study adopts a cross-sectional design, which can only reflect patient perceptions at a specific time point and is difficult to capture the long-term dynamic evolution of the impact of medical configuration optimization on the doctor-patient relationship. Subsequent research may consider using a longitudinal tracking design to deeply verify the stability of the causal relationship. In addition, data collection is entirely dependent on patients' self-assessment, which may introduce subjective biases or social expectations. In the future, multi-source data comparisons can be conducted alongside objective clinical indicators or evaluations from the medical staff's perspective. Finally, this study mainly focuses on the mediating mechanism and has not delved deeply into the moderating role of individual values, such as digital literacy or secular rationality, in the path. Future research should focus on identifying these boundary conditions to construct more explanatory moderated-mediation models.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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