Analysis of Factors Influencing Residents' Dental Health Based on Water Quality Using Principal Component Analysis and Structural Equation Modeling

Lili Li #, *, Hongxiang Su #, Yutong Ren #

Heze University, Heze, Shandong 274000, China

* Corresponding Author: Lili Li (Email: ruby0538@126.com)

#The three authors have made the same contribution to this article

Abstract. To explore the correlation mechanism between water quality and residents' dental health in XX City, identify the core influencing factors of water quality and the action paths of dental protection measures, and provide a scientific basis for formulating integrated intervention strategies, this study conducted a systematic quantitative analysis. A total of 758 valid questionnaires were collected online. After verifying reliability and validity via Bartlett's sphericity test and the KMO test, principal component analysis (PCA) was used to condense the social factors affecting water quality. Subsequently, a structural equation model (SEM) was constructed to verify the hypothesized relationships. The results indicated that water conservancy institutions, industrial impact, and government management are the core factors influencing water quality. The structural equation model exhibited excellent goodness-of-fit, and a significant positive linear impact of "Dental Health-Life Association" on "Dental Protection Measures" was identified. The analytical framework of "data verification, factor extraction, and relationship modeling" established in this study provides a replicable quantitative research paradigm for improving regional water quality and promoting residents' oral health.

Keywords: XX Water Quality; Residents' Dental Health; Reliability and Validity Tests; Principal Component Analysis; Structural Equation Modeling.

1. Introduction

Water resources are fundamental to residents' health, and water quality status[1]is directly linked to human health. Issues such as excessive fluoride in drinking water and leakage of industrial pollutants have been confirmed to be closely associated with oral diseases like dental fluorosis[2]and caries. XX City is located in the Yellow River Flood Plain, relying primarily on surface and groundwater. It currently faces challenges including agricultural non-point source pollution of surface water, industrial wastewater[3]discharge, and fluoride/nitrate exceedances due to groundwater over-extraction[4]. Dental health problems among local residents are prominent, with a caries prevalence rate of 53.12% in children aged 4-6[5], and an oral disease prevalence rate exceeding 90% among the elderly. The risk of dental fluorosis is highly correlated with high-fluoride groundwater.

From a practical perspective, improving water quality and enhancing residents' dental health require clarifying the pathways of influence between them and the relative importance of various social stakeholders (government, water conservancy institutions, industry, agriculture, individuals) in maintaining water quality. Academically, there is a need to establish scientific quantitative models to systematically analyze the relationships among multiple factors. Therefore, this study is significant for addressing practical livelihood issues in XX City and refining quantitative analysis methods in the "environment and health" domain.

Existing research has three main shortcomings: Firstly, most studies focus separately on either water quality influencing factors or residents' dental health, lacking a systematic analysis of the entire chain linking "water quality, social factors, dental health, protection measures". Secondly, while PCA in water quality research is often used for indicator condensation, and SEM in the health field is often used to verify behavior-health relationships, studies combining both—first extracting core water quality factors and then verifying the relationship between dental health and protection measures—

are scarce. Thirdly, there is insufficient regional research focused on cities like XX City in the Yellow River Flood Plain, making it difficult to directly support the formulation of local intervention strategies.

Constructed a progressive analytical framework of "reliability/validity tests, principal component analysis, structural equation modeling," achieving a full-process quantitative study from data verification to factor extraction and relationship modeling, filling the gap in cross-domain systematic analysis of "water quality, dental health".

For the first time, specifically identified the relative weights of social stakeholders like water conservancy institutions, industry, and government in maintaining water quality in XX City, providing data support for differentially formulating water quality improvement measures.

Verified the linear impact relationship of "Dental Health-Life Association" on "Dental Protection Measures" (model fit reached excellent levels), providing a theoretical basis for promoting residents' proactive adoption of dental protection measures.

2. Related Theories

2.1 Principal Component Analysis [6]

Principal Component Analysis is a multivariate statistical method that transforms multiple potentially correlated original variables into a set of linearly uncorrelated new variables (principal components) via linear transformation. These new variables are sorted in descending order of variance contribution. The first few principal components can retain most of the information from the original variables, achieving data dimensionality reduction and core factor extraction.

Let the original variables be $X_1, X_2, ..., X_P$ (where P is the number of variables).After standardization, we obtain $x_1, x_2, ..., x_p$ .The linear combination expression for the principal component $Z_1, Z_2, ..., Z_m$ ($m < p$)is:

$$\begin{cases} Z_1 = a_{11}x_1 + a_{12}x_2 + ... + a_{1p}x_p \\ Z_2 = a_{21}x_1 + a_{22}x_2 + ... + a_{2p}x_p \\ ... \\ Z_m = a_{m1}x_1 + a_{m2}x_2 + ... + a_{mp}x_p \end{cases} \tag{1}$$

where: Z_i is the i -th principal component; a_{ij} is the loading coefficient of the i -th principal component corresponding to the j -th original variable,satisfying $\sum_{j=1}^{p} a_{ij}^2 = 1$ the principal components are uncorrelated with each other($Cov(Z_i, Z_j) = 0, i \neq j$),and the variance of Z_1 is maximized($Var(Z_1) \geq Var(Z_2) \geq ... \geq Var(Z_m)$).

The variance contribution rate $\lambda_i / \sum_{k=1}^{p} \lambda_k$ of a principal component(λ_i is the i -th eigenvalue of the covariance matrix)is used to measure the degree to which it retains original information. Principal components with a cumulative variance contribution rate $\geq$ 60% can be used as core analysis variables.

Reasons for choosing PCA: Firstly, this study involves five water quality influencing factors (government, water conservancy institutions, industry, agriculture, individuals), among which correlations may exist; PCA can effectively eliminate multicollinearity. Secondly, this method can quantify the importance of each factor through variance contribution rates, providing an objective basis for determining the core influencing entities. Its advantages include: strong interpretability of results, retention of most original information, concise calculation process, and suitability for linkage with subsequent SEM.

2.2 Structural Equation Modeling [7]

Structural Equation Modeling is a multivariate statistical model integrating factor analysis and path analysis. It can simultaneously handle latent variables (variables that cannot be directly measured) and manifest variables (directly observable variables), testing preset relationships between variables through confirmatory analysis, making it suitable for quantitative verification of complex causal relationships.

SEM consists of two parts: measurement equations and structural equations:

1.Measurement Equations (relationships between latent and manifest variables):

$$Y = \Delta_Y \eta + (2\varepsilon) \tag{2}$$

$$X = \Delta_X \xi + (3\delta) \tag{3}$$

2.Structural Equation (causal relationships between latent variables):

$$\eta = B\eta + \Gamma\xi + (4\zeta) \tag{4}$$

where: Y is the vector of endogenous manifest variables (e.g., "brushing frequency", "water quality improvement behavior"), X is the vector of exogenous manifest variables (e.g., "age", "residence"); η is the vector of endogenous latent variables (e.g., "Dental Protection Measures"), ξ is the vector of exogenous latent variables (e.g., "Dental Health-Life Association"); Δ_Y is the loading matrix of endogenous manifest variables on endogenous latent variables, Δ_X is the loading matrix of exogenous manifest variables on exogenous latent variables; B is the path coefficient matrix between endogenous latent variables, Γ is the path coefficient matrix of exogenous latent variables on endogenous latent variables; ε、δ is the vector of measurement errors, ζ is the residual vector of the structural equation, and ε, δ, ζ are uncorrelated.

Reasons for choosing SEM: Firstly, "Dental Health-Life Association" and "Dental Protection Measures" in this study are latent variables, requiring indirect measurement through multiple manifest variables; this model can handle both latent and manifest variables simultaneously. Secondly, there is a need to verify the linear relationship between them; the path analysis function of SEM can quantify the causal effect. Its advantages include: tolerance for multicollinearity, comprehensive assessment of model validity through fit indices, and results that intuitively reflect the strength of relationships between variables, providing a scientific tool for verifying the "dental health and protection measures" relationship.

3. Experimental Section

3.1 Experimental Overview

This experiment aimed to verify the effectiveness of PCA in extracting core water quality influencing factors and the reliability of SEM in verifying the impact of "Dental Health-Life Association"[8]on "Dental Protection Measures". The experimental steps were as follows: first, introduce the source and structure of the questionnaire dataset; second, set evaluation indicators for reliability/validity tests, PCA, and SEM; finally, analyze core results and verify model performance through data calculation and model fitting.

3.2 Dataset Description

The experimental data came from an online questionnaire survey of residents in XX City. The survey covered both local and non-local residents and included three main dimensions: "Water Quality-Social Aspects Association", "Dental Health-Life Association", and "Dental Protection Measures". 800 questionnaires were distributed, and 758 valid questionnaires were recovered, yielding an effective response rate of 94.75%. The basic characteristics of the sample aligned with the demographic structure of XX City, ensuring data representativeness.

3.3 Core Model Experiments and Results

3.3.1 Data Preprocessing

This study used Bartlett's sphericity test and the KMO measure. KMO values of 0.6-0.7, 0.7-0.8, and >0.9 indicate mediocre, good, and very good validity, respectively. A Bartlett's test statistic closer to 1 indicates better results. Reliability and validity tests were conducted on the pre-survey questionnaire, with results as follows:

(1) Reliability Test

Table 1. Cronbach's Alpha Coefficients for Pre-survey Variables

Questionnaire for Residents of XX City		
Category	Cronbach'a	Number of Items
Importance of Water Quality-Social Aspects Association	0.906	5

As shown in Table 1, the Cronbach's α coefficient for the category variable in this questionnaire is greater than 0.6. Therefore, the questionnaire passes the reliability test.

(2) Validity Test

Table 2. Pre-survey Validity Test Results

Questionnaire for Residents of XX City		
KMO Measure of Sampling Adequacy		0.874
KMO Bartlett's Test of Sphericity	Approx. Chi-Square	3526.5
	df	721
	Sig.	0.000

As shown in Table 2, the significance level of Bartlett's test for the questionnaire is less than 0.05, and the KMO value is greater than 0.8, indicating good pre-survey validity; the questionnaire passes the validity test.

(3) Reliability Analysis for Association Importance

Table 3. Importance of Water Quality-Social Aspects Association

Option	Corrected Item Total Correlation	Squared Multiple Correlation	Cronba-ch's Alpha if Itm Deleted	Standardiz-ed α
Govern-ment	0.731	0.694	0.84	0.876
Water Institutions	0.797	0.675	0.824	
Industry	0.771	0.641	0.831	
Agricult-ure	0.695	0.534	0.849	
Individu-al	0.535	0.428	0.887	

As shown in Table 3, the overall standardized reliability coefficient for the importance of water quality-social aspects association is 0.876. Based on the reliability coefficients after item deletion, most values are less than the overall 0.876. The reliability coefficient ranges from 0 to 1, with values closer to 1 indicating higher reliability. The result of 0.876 indicates relatively good reliability.

3.3.2 Principal Component Analysis Experiment (Extracting Water Quality Influencing Factors)

1. Model Construction Process

Variable Selection: "Government Management", "Role of Water Conservancy Institutions[9]", "Industrial Impact[10]", "Agricultural Impact[11]", and "Individual Behavior[12]" were selected as original variables, denoted ($X_1 - X_5$), all measured on a 5-point Likert scale (1=Extremely Unimportant, 5=Extremely Important).

Data Preprocessing: Original variables were standardized to eliminate scale differences; the KMO test and Bartlett's sphericity test were used to verify data suitability for PCA (results in Table 2).

Parameter Setting: The eigenvalues and eigenvectors of the covariance matrix were calculated using SPSS software. Principal components were extracted based on the "eigenvalue ≥ 1" criterion. Loadings, communalities, and weights for each variable were calculated.

2. Experimental Results and Analysis

Table 4. KMO and Bartlett's Test

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		0.778
Bartlett's Test of Sphericity	Approx. Chi-Square	2185.255
	df	10
	Sig.	0

PCA explores how quantitative data can be condensed into a few components. Typically, for weight calculation: First, analyze the KMO value; if above 0.8, it is very suitable; between 0.7~0.8, moderately suitable; between 0.6~0.7, acceptable; below 0.6, unsuitable. Second, if the Bartlett's test p-value is less than 0.05, it is suitable for PCA. Third, if there are only two analysis items, the KMO is always 0.5.

Table 5. Principal Component Extraction Analysis

	Extraction Sums of Squared Loadings		
No.	Eigenvalue	Variance%	Cumulative%
1	3.365	67.298	67.298
2	-	-	-
3	-	-	-
4	-	-	-
5	-	-	-

To conduct PCA for information condensation, first analyze if the data is suitable. From Table 5: KMO is 0.778 (>0.6), meeting the prerequisite for PCA, meaning the data can be used for PCA. The data also passed Bartlett's test ($p<0.05$), indicating suitability for PCA.

Table 6. Communalities of Various Dimensions

Name	Loading Coefficient	Communality
	Component 1	
Government	0.852	0.725
Water Institutions	0.886	0.784
Industry	0.870	0.756
Agriculture	0.805	0.648

Table 6 analyzes the principal component extraction and the amount of information extracted. From the table, one principal component was extracted, with an eigenvalue greater than 1. Its weighted variance explanation rate (weight) is: 67.298 / 67.298 = 100.00%.

Table 7 shows the information extraction of the research items by the principal component and the relationship between the principal component and the research items. All research items have communality values above 0.4, indicating a strong association between the items and the principal component. Variables like Government, Water Institutions, Industry, Agriculture, and Individual all have significant associations with the extracted principal component.

Table 7. Component Score Coefficients for Various Dimensions

Name	Component
	Component 1
Government	0.464
Water Institutions	0.483
Industry	0.474
Agriculture	0.439
Individual	0.366

The original variables were standardized to eliminate scale effects. The standardized variable ZX_i is:

$$ZX_i = \frac{X_i - \mu_i}{\sigma_i}, i = 1,2,3,4,5 \tag{5}$$

where μ_i is the mean of variable X_i, and σ_i is the standard deviation of variable X_i.

After PCA, the extracted first principal component (PC1) is a linear combination of these standardized variables. Its general form is:

$$\mathrm{PC1} = \mathrm{l_1} \cdot \mathrm{ZX_1} + \mathrm{l_2} \cdot \mathrm{ZX_2} + \mathrm{l_3} \cdot \mathrm{ZX_3} + \mathrm{l_4} \cdot \mathrm{ZX_4} + \mathrm{l_5} \cdot \mathrm{ZX_5} \tag{6}$$

where $\mathrm{l_1}, \mathrm{l_2}, \ldots, \mathrm{l_5}$ are the loading coefficients, constituting the eigenvector corresponding to the eigenvalue.

The formula for calculating the comprehensive score coefficient$\mathrm{w_i}$is:

$$\mathrm{w_i} = \frac{\mathrm{l_i}}{\sqrt{\lambda_1}}, \mathrm{i} = 1,2,3,4,5 \tag{7}$$

Finally, the formula for calculating the comprehensive score Z for each sample is the linear combination of these comprehensive score coefficients and the standardized variables:

$$\mathrm{Z} = \mathrm{w_1} \cdot \mathrm{ZX_1} + \mathrm{w_2} \cdot \mathrm{ZX_2} + \mathrm{w_3} \cdot \mathrm{ZX_3} + \mathrm{w_4} \cdot \mathrm{ZX_4} + \mathrm{w_5} \cdot \mathrm{ZX_5} \tag{8}$$

where Zrepresents the extracted principal component, synthesizing information from multiple aspects including government management, role of water institutions, industrial impact, agricultural impact, and individual behavior, with a variance explanation rate of 67.298%.

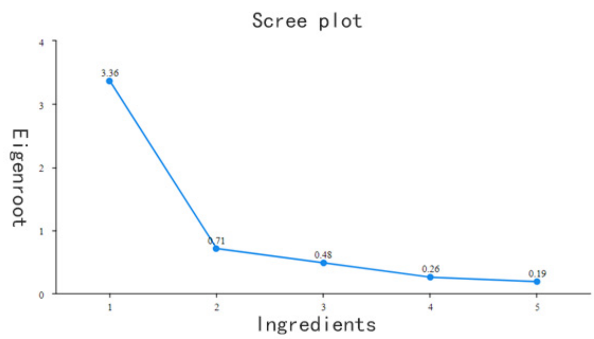

Figure 1. Scree Plot

The extracted principal component$\mathrm{Z}$comprehensively reflects the social factors affecting water quality. Among them, Water Institutions have the highest weight (0.483), indicating they play the most critical role. Government Management (0.464) and Industrial Impact (0.474) also have high weights, signifying their important roles in maintaining water quality. Agricultural Impact (0.439) and Individual Behavior (0.366), while having slightly lower weights, still exert non-negligible influences on water quality.

From the scree plot, we observe that the eigenvalue of the first principal component is 3.36, significantly higher than the others, indicating it explains most of the variation in the data. Starting from the second principal component, eigenvalues drop rapidly (the second PC's eigenvalue is 0.71). The eigenvalues of the fourth and fifth components show a gradually decreasing trend, but the rate of decrease slows. The scree plot helps determine the number of components to extract; the point where the line transitions from steep to flat suggests the number of components to retain is one.

Model result analysis yields:

Table 8. Linear Combination Coefficient Matrix

Name	Component 1	Comprehensive Score Coefficient	Weight
Eigenvalue	3.365		
Variance Explained	67.30%		
Government	0.4643	0.4643	20.86%
Water Institutions	0.4828	0.4828	21.69%
Industry	0.4741	0.4741	21.30%
Agriculture	0.4390	0.4390	19.72%
Individual	0.3660	0.3660	16.44%

1.Linear Combination Coefficient Matrix: The "Eigenvalue" in Table 8 corresponds to "eigen" in step one. The "Linear Combination Coefficient" corresponds to the "loading matrix / Sqrt(eigen)", i.e., the loading coefficient divided by the square root of the corresponding eigenvalue.

2.Comprehensive Score Coefficients: Calculated via the formula in step two, "(Cumulative(Linear Combination Coefficient * Variance Explained)) / Cumulative Variance Explained", resulting in coefficients for Government, Water Institutions, Industry, Agriculture, and Individual of 0.4643, 0.4828, 0.4741, 0.4390, and 0.3660, respectively.

3.Weight Calculation: Weights were obtained through normalization in step three, normalizing the comprehensive score coefficients. The resulting weights are: Government 20.86%, Water Institutions 21.69%, Industry 21.30%, Agriculture 19.73%, Individual 16.44%. This indicates that all social aspects have considerable importance in their association with water quality.

3.3.3 Structural Equation Model Experiment (Verifying Dental Health and Protection Measures Relationship)

1. Model Construction Process

1.Latent and Manifest Variable Specification:Exogenous Latent Variable ξ: "Dental Health-Life Association", corresponding to manifest variables X_1 (Age), X_2 (Residence), X_3 (Teeth Cleaning Habits), X_4 (Drinking Water Type).Endogenous Latent Variable η: "Dental Protection Measures", corresponding to manifest variables Y_1 (Brushing Teeth on Time), Y_2 (Using Dental Floss), Y_3 (Regular Dental Check-ups), Y_4 (Paying Attention to Water Quality Improvement).

2.Model Preset: It was hypothesized that ξ has a positive linear impact on η (path coefficient $\gamma_{11} > 0$). Measurement errors ε、δ were assumed to be uncorrelated.

3.Parameter Estimation and Goodness-of-fit Test: Parameters were estimated using the maximum likelihood method. Model fit was evaluated using CMIN/DF, RMSEA, CFI, and TLI indices (Evaluation criteria: CMIN/DF 1-3 Excellent, RMSEA<0.05 Excellent, CFI, TLI>0.9 Excellent).

2. Experimental Results and Analysis

The goodness-of-fit test results for the SEM model of dental health and protection influencing factors are shown in the table below:

Table 9. Model Goodness-of-Fit Indices

Fit Index		
CMIN/DF	1-3 Excellent, 3-5 Good	1.414
RMSEA	<0.05 Excellent, <0.08 Good	0.038
IFI	>0.9 Excellent, >0.8 Good	0.986
TLI	>0.9 Excellent, >0.8 Good	0.982
CFI	>0.9 Excellent, >0.8 Good	0.985
Fit Index	Reference Standard (Excellent/Good)	Result Value

As shown in Table 9, all fit indices reached excellent levels, indicating an extremely good fit between the model and the data, making it suitable for verifying relationships between variables. CMIN/DF (Chi-square/Degrees of Freedom) = 1.414, within the 1-3 range, indicates small overall model fit error and minor differences between the observed data and the model's preset covariance structure. RMSEA (Root Mean Square Error of Approximation) = 0.038, within the <0.05 excellent range, indicates minimal model approximation error and strong model fit.

Additionally, the IFI, TLI, and CFI results all reached excellent levels above 0.9, indicating an extremely good model fit to the data. The model effectively explains the covariance relationships among variables. Therefore, based on these results, the dental health CFA model has good fit and reasonably reflects the real data structure.

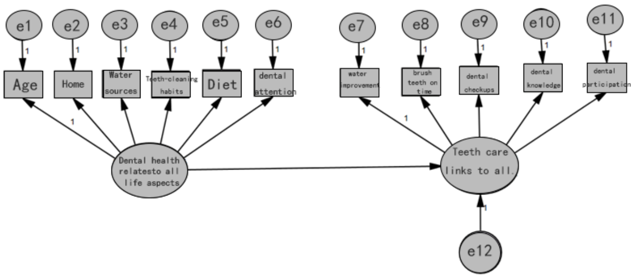

Figure 2. SEM Model Path Relationship Hypothesis Test Results for Dental Protection Influencing Factors

From Figure 2, the standardized path coefficient from the exogenous latent variable "Dental Health-Life Association" to the endogenous latent variable "Dental Protection Measures" is 0.62 ($p < 0.001$), indicating a significant positive linear relationship. The higher the residents' awareness of the "Dental Health-Life Association", the stronger their initiative to adopt "Dental Protection Measures", verifying the preset causal relationship.

3.4 Experimental Summary

Through the experimental design and analysis using PCA and SEM, the weights of core water quality influencing factors and the relationship path between dental health and protection measures were obtained. The results show that PCA effectively condenses water quality influencing factors, and SEM reliably verifies causal relationships between complex variables. The combination of these two models provides an effective quantitative tool for studying the "water quality-dental health" association.

4. Conclusion

Through reliability/validity tests, PCA, and SEM experiments on 758 resident questionnaires from XX City, the following results were obtained:

1.Good reliability and validity of questionnaire data: In the reliability test, the Cronbach's α coefficient for the "Importance of Water Quality-Social Aspects Association" category was 0.906 >

0.6. In the validity test, the KMO value was 0.874 > 0.8, and Bartlett's test p-value was 0.000 < 0.05, indicating that data reliability and validity meet the requirements for subsequent analysis.

2.Clear core water quality influencing factors: PCA extracted one core principal component (variance explained 67.298%). The weight ranking of social factors is: Water Institutions (21.69%) > Industry (21.30%) > Government (20.86%) > Agriculture (19.72%) > Individual (16.44%). This indicates that the role of water institutions in maintaining water quality is most critical, while industrial pollution control and government management need simultaneous strengthening.

3.Significant relationship between dental health and protection measures: The SEM showed excellent fit (CMIN/DF=1.414, RMSEA=0.038). The standardized path coefficient from "Dental Health-Life Association" to "Dental Protection Measures" was 0.62 (p<0.001), indicating that residents' awareness of the link between dental health and life significantly promotes the adoption of dental protection measures.

4.Close association between water quality and dental health: Combining the current water quality status in XX City (groundwater fluoride exceedance, surface water pollution) with resident dental health data (children's caries rate 53.12%, elderly oral disease rate >90%), it can be inferred that water quality issues like high-fluoride groundwater and industrial pollution are important contributing factors to dental fluorosis and caries.

Based on the above analysis, it can be concluded that XX City needs to focus on water institutions as the core, with multi-departmental collaboration to promote water quality improvement, while simultaneously strengthening publicity about the "water quality-dental health" link to effectively enhance regional water quality and residents' oral health levels.

5. Summary

In this paper, we investigated the correlation mechanism between water quality and residents' dental health in XX City based on 758 resident questionnaires, employing a progressive methodology of "reliability/validity tests, principal component analysis, structural equation modeling". The core conclusions are: Water institutions are the primary influencing factor for water quality, and residents' awareness of the link between dental health and life significantly promotes the adoption of dental protection measures. The innovation of this research lies in combining two statistical models to achieve a full-process analysis, providing a replicable framework for the integrated management of "water quality and health" in similar cities. Future work could expand the sample size, incorporate physicochemical water quality monitoring data, construct more precise three-dimensional models, and extend the research to other similar cities in the Yellow River Flood Plain, providing broader support for relevant policy formulation.

References

[1] Hou S, Zhou Q. Analysis of Surface Water Resource Quality and Protection Measures in Heze City. [J] Water Safety. 2023, (06):45-52.

[2] Li L, Chen M. Correlation between Fluoride Content in Drinking Water and Dental Fluorosis. [J] Journal of Environment and Health. 2022, 39(04): 321-325.

[3] Zhang W, Liu M. Impact Analysis of Industrial Wastewater Discharge on Regional Surface Water Quality. [J] Chinese Journal of Environmental Engineering, 2021,15(08): 2643-2650.

[4] Zhao J, Wu G. Water Quality Problems and Governance Countermeasures Induced by Groundwater Over-exploitation in the Yellow River Flood Plain. [J] Water Resources Protection, 2020,36(03): 89-95.

[5] Chen Y, Ma T. An Epidemiological Survey on the Current Status and Influencing Factors of Dental Caries in Children. [J] Maternal and Child Health Care of China,2023,38(11): 2056-2059.

[6] Liu J, Sun W. Application of Principal Component Analysis in Extracting Water Quality Influencing Factors. [J] Statistics and Decision, 2022,38(17): 156-159.

[7] Wang H, Zhang Y. Application and Practice of Structural Equation Modeling in the Health Field. [J] Science Press. 2024.

[8] Wang L, Zhou X. Correlation Analysis between Residents' Oral Health Awareness and Dental Protection Behaviors. [J] Chinese Journal of Public Health, 2021,37(09): 1368-1371.

[9] Han X, Dong L. Functional Positioning and Role Fulfillment of Water Conservancy Institutions in Water Resource Protection. [J] Water Resources Development Research, 2022,22 (05): 43-47.

[10] Zhang Z, Pan Q. Contribution of Industrial Wastewater Segregation to Influent BOD_5 of Water Purification Plants. [J] China Municipal Engineering, 2022,46 (10): 56-60.

[11] Wu M, Zheng T. Impact of Agricultural Non-point Source Pollution on Surface Water Quality and Control Measures. [J] Journal of Agro-Environment Science, 2021,40 (06): 1201-1208.

[12] Ma L, Chen F. Research on the Influence of Personal Behavioral Factors on Drinking Water Quality Safety. [J] Chinese Journal of Public Health Engineering, 2023,22 (02): 251-254.