

Nonlinear analysis of factors influencing tuberculosis outpatient visits in China: an explainable machine learning approach

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Abstract

This study aims to analyze the temporal trends, interprovincial differences, and key predictors of Tuberculosis Outpatient Visits (TOV) in China. It provides empirical evidence for understanding regional differences in tuberculosis-related outpatient service utilization. Panel data from 30 Chinese provinces from 2012 to 2024 were used. The study included variables related to economic development, health resources, education resources, environmental governance, pollutant emissions, and technological innovation. Correlation analysis, model comparison, and XGBoost-SHAP analysis were applied. From 2012 to 2024, TOV showed a gradual upward trend and clear interprovincial differences. Shanghai, Fujian, Guangdong, and Zhejiang had relatively higher total recorded outpatient volumes. XGBoost showed the best predictive performance among all candidate models ($R^2 = 0.8154$). SHAP results identified Disposable Income Per Capita (DIPC), University Staff (USTF), Domestic Patent Applications (DPA), Hospital Beds (HBED), and Technology Market Turnover (TMT) as the main predictors. Environmental governance and pollutant emission variables had lower overall contributions, but they still showed nonlinear predictive contributions in some value ranges. The findings suggest that interprovincial differences in TOV are jointly associated with economic development, health resources, education resources, environmental governance, and technological innovation. TOV mainly reflects outpatient service utilization and case detection capacity. It should not be interpreted as a direct measure of tuberculosis incidence risk.

Key words: tuberculosis outpatient visits; outpatient service utilization; XGBoost-SHAP; predictors.

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Introduction

Tuberculosis remains a major infectious disease and public health concern worldwide. It is also a key focus of the World Health Organization End TB Strategy and Sustainable Development Goal 3 (SDG 3). In recent years, progress has been made in diagnosis, treatment, and management. However, under-detection, diagnostic delay, discontinuity of care, and regional differences in control capacity remain important challenges. The Global Tuberculosis Report 2024 emphasizes that tuberculosis control should not only focus on incidence, mortality, and disease burden. It should also improve case detection, diagnostic access, and continuity of health service management (World Health Organization, 2024). China is one of the countries with a high tuberculosis burden. Previous research shows that newly notified tuberculosis cases in China have generally declined, but clear regional differences remain. Some regions continue to face substantial tuberculosis control pressure (Wang *et al.*, 2021). Existing studies have mainly examined tuberculosis through incidence, notified cases, disease burden, and spatial clustering. They have also found associations between tuberculosis and population structure, socioeconomic conditions, health resources, and environmental factors (Deng *et al.*, 2024; Guo *et al.*, 2025; Huang *et al.*, 2024). However, tuberculosis control is not only related to disease occurrence. It is also related to case detection, diagnostic service use,

and health system response capacity. Unlike incidence, Tuberculosis Outpatient Visits (TOV) reflect disease-related medical demand and outpatient service utilization. The recorded volume of TOV may vary with access to care, case-detection and reporting capacity, health-seeking behavior, and diagnostic delay (World Health Organization, 2024; X. Chen *et al.*, 2024; L. Zhang *et al.*, 2024; Fan *et al.*, 2025). Population mobility and the regional concentration of health resources may further contribute to geographical differences in TOV (Jiang *et al.*, 2025; X. Chen *et al.*, 2024). A higher TOV does not necessarily indicate a higher incidence risk. It may also reflect stronger service absorption capacity and better case detection. In contrast, a lower TOV may reflect insufficient service use, diagnostic delay, or under-detection. Therefore, studying TOV can complement studies based on incidence and disease burden. It can help explain regional differences in tuberculosis-related outpatient service utilization. Against this background, this study uses panel data from 30 Chinese provinces from 2012 to 2024. It takes TOV as the outcome variable. Correlation analysis, model comparison, and the XGBoost-SHAP method are used to examine temporal trends, interprovincial differences, and related predictors of TOV. Compared with previous research, this study makes three contributions. First, the study uses TOV as an indicator of tuberculosis-related service utilization. This differs from most previous studies, which focused on incidence, notified cases, or disease burden. TOV can reflect out-

patient service use, case detection capacity, and health system responsiveness. It therefore offers a service-utilization perspective for understanding regional differences in tuberculosis control in China. Second, the study uses long-term provincial panel data from 2012 to 2024. It examines temporal changes and interprovincial differences in TOV. Many existing spatiotemporal studies of tuberculosis focus on single provinces, cities, or counties. National-level long-term comparisons across provinces remain limited. This study therefore provides a broader view of regional differences in tuberculosis-related outpatient service utilization. Third, this study applies XGBoost-SHAP to the analysis of tuberculosis outpatient service utilization. XGBoost can capture nonlinear relationships and interactions between TOV and multidimensional factors such as socioeconomic development, health resources, education resources, environmental governance, pollutant emissions, and technological innovation. SHAP further explains the direction and magnitude of each variable's contribution to model predictions. This approach combines predictive performance with interpretability. It provides a useful tool for identifying related predictors and nonlinear predictive contributions in TOV.

Literature review

Tuberculosis epidemiology in China

Existing tuberculosis research has mainly focused on trends, disease burden, spatial and temporal patterns, and related factors. Wang *et al.* (2021) found that newly notified tuberculosis cases in China generally declined, but regional differences remained. Deng *et al.* (2024) reported that population structure, socioeconomic conditions, and health resources were associated with tuberculosis incidence in mainland China. Guo *et al.* (2025) and R. Sun *et al.* (2025) further showed that the tuberculosis burden in China has declined overall, but regional imbalance and control pressure persist. These studies provide important evidence for understanding the epidemiological profile of tuberculosis in China. However, most of them used incidence, notified cases, or disease burden as outcomes. Fewer studies have examined tuberculosis outpatient visits from a health service utilization perspective. Studies of incidence and disease burden can provide useful background for understanding regional differences in TOV, but TOV more directly reflects outpatient service use and case detection capacity.

Spatial and temporal patterns of tuberculosis

In terms of spatial patterns, previous studies generally show that tuberculosis has clear spatial heterogeneity and clustering. Huang *et al.* (2024) identified significant spatial differences in pulmonary tuberculosis in Hunan Province. J. Zhang *et al.* (2024) found that tuberculosis distribution in Dongguan was associated with population, economic, and social conditions. Wang *et al.* (2025), K. Zhang *et al.* (2025), and Pan *et al.* (2024) also identified spatial clustering and temporal fluctuations in Hubei, Shaoxing, and Pudong New Area of Shanghai. However, these studies were mostly conducted at the provincial, city, or county level in specific regions. Long-term panel studies at the national provincial level remain relatively limited.

Socioeconomic, health-system, and environmental determinants

Tuberculosis diagnosis and management are also associated with socioeconomic conditions and health-system capacity. Wu *et*

al. (2023), Ferreira *et al.* (2023), and Xu *et al.* (2023) reported associations of poverty, social protection, and financial burden with healthcare seeking and treatment continuity among patients with tuberculosis. Jiang *et al.* (2025), Fan *et al.* (2025), and X. Chen *et al.* (2024) further identified associations of population mobility, health-system delay, and primary-care capacity with case detection and diagnostic efficiency. However, how these multidimensional regional characteristics are associated with provincial TOV remains insufficiently examined.

Machine-learning applications in tuberculosis research

Methodologically, traditional spatial statistics and regression models can identify linear associations. However, they are limited in handling high-dimensional variables, nonlinear relationships, and interactions. XGBoost can model complex feature structures and nonlinear relationships (Chen & Guestrin, 2016). SHAP is based on the Shapley value framework and can explain model predictions by quantifying the marginal contribution of each variable (Lundberg & Lee, 2017). Explainable machine learning has been used to predict tuberculosis treatment failure, drug-induced liver injury, loss to follow-up, and outcomes in HIV/TB co-infection (Peng *et al.*, 2024; Xiao *et al.*, 2024; J. Chen *et al.*, 2024; Q. Sun *et al.*, 2025). Yet most of these studies focused on individual clinical outcomes. Few have applied machine learning to provincial-level public health service utilization.

In summary, several gaps remain. First, most studies focus on incidence, notified cases, or disease burden. Few examine TOV as an indicator of service utilization. Second, many spatiotemporal studies focus on local areas, while national long-term provincial panel studies are limited. Third, traditional models have limited ability to identify nonlinear relationships and variable interactions. Fourth, machine learning has rarely been used to analyze provincial-level tuberculosis service utilization. To address these gaps, this study uses panel data from 30 Chinese provinces from 2012 to 2024. It applies XGBoost-SHAP to examine temporal trends, interprovincial differences, and related predictors of TOV.

Materials and Methods

Methodology

This study uses an XGBoost-SHAP framework to analyze temporal trends, interprovincial differences, and related predictors of TOV across Chinese provinces. TOV reflects tuberculosis-related outpatient service utilization. It may also be associated with economic development, income, health resource allocation, education resources, environmental exposure, and technological innovation. These factors may have nonlinear relationships and complex interactions. Traditional linear models may not fully capture these patterns. Therefore, after descriptive statistics and correlation analysis, this study builds XGBoost regression models and uses SHAP to interpret model predictions.

XGBoost is a gradient boosting tree-based ensemble learning method proposed by Chen and Guestrin (2016). It can handle nonlinear relationships, variable interactions, and complex feature structures. Compared with ordinary linear regression, XGBoost does not require a strict linear relationship between predictors and the outcome. It is therefore suitable for exploring complex associations between TOV and multidimensional socioeconomic and environmental factors. To improve model interpretability, this

study uses SHAP (Lundberg & Lee, 2017). Following the use of XGBoost-SHAP in tuberculosis prediction by Peng *et al.* (2024), SHAP values are used to quantify the marginal contribution of each variable to model predictions. SHAP values reflect contributions to model predictions, not causal effects (Lundberg & Lee, 2017). Thus, XGBoost-SHAP is used here as an interpretive tool to identify related predictors and explore potential nonlinear patterns in TOV.

Specifically, the study first organized panel data for 30 Chinese provinces from 2012 to 2024. Variable units and data formats were checked for consistency before model development. TOV was used as the dependent variable. Variables related to economic development, income, health resources, education resources, environmental pollution governance, pollutant emissions, and technological innovation were used as predictors. Linear regression, ridge regression, lasso regression, KNN, random forest, gradient boosting, and XGBoost models were constructed. Model performance was evaluated using R^2 , RMSE, MAE, and MSE. After XGBoost was identified as the best-performing model, SHAP values were calculated. SHAP summary plots and dependence plots were then used to examine the magnitude, direction, and nonlinear patterns of the main predictors. The dataset was randomly divided into a training set (80%) and an independent test set (20%) using a fixed random seed of 42. All candidate models were evaluated using the same partition. The XGBoost model was configured with 100 estimators, a maximum tree depth of 6, a learning rate of 0.1, a subsample ratio of 0.8, and a column-sampling ratio of 0.8. Five-fold

cross-validation was conducted within the training set using shuffled folds and a fixed random seed of 42. The final model was fitted using the complete training set and evaluated on the independent test set. The analytical workflow is shown in Figure 1.

Variables

The study area consisted of provincial administrative units in China. Data were obtained from the China Statistical Yearbook and the China Health Statistical Yearbook. The dataset covered 30 Chinese provinces from 2012 to 2024. Hong Kong, Macao, Taiwan, and Tibet were excluded. The data were organized as panel data.

At the provincial level, the outcome variable was Tuberculosis Outpatient Visits (TOV), expressed in 10^4 visits. TOV was defined as the annual volume of tuberculosis-related outpatient encounters recorded in each province and was used to represent the overall utilization of tuberculosis outpatient services rather than the number of unique patients. TOV was analyzed as the total recorded outpatient volume and was not standardized by provincial population; therefore, provincial comparisons refer to differences in total service volume rather than per-capita healthcare utilization. The province-year observations were pooled because the primary objective was to examine overall predictive associations between regional characteristics and TOV across the study period, rather than to estimate causal temporal effects or develop a time-series forecasting model. To assess whether calendar time provided additional predictive information, a sensitivity analysis was conducted by including Year as an

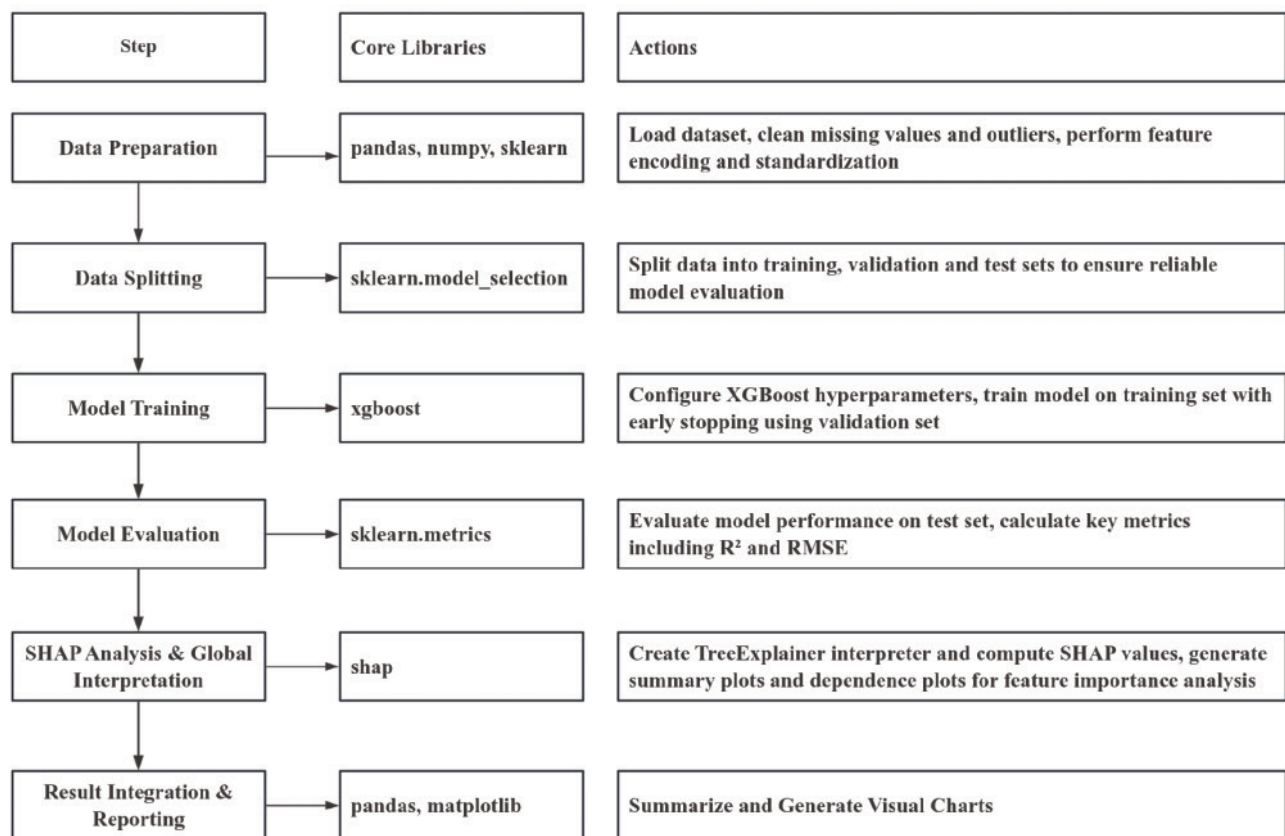


Figure 1. XGBoost-SHAP analysis workflow.

additional predictor in the XGBoost model while retaining the same training–test split and hyperparameter settings. Lagged predictors were not included because no specific lag structure was prespecified and the study was not designed to estimate delayed or causal effects. Predictors were selected from six dimensions: socioeconomic development, health resources, education resources, environmental governance, pollutant emissions, and technological innovation. Economic variables included GDP Per Capita (GDPPC) and Disposable Income Per Capita (DIPC). Health resource variables included Health Technicians per 10,000 Population (HTTP) and hospital beds (HBED). Education variables included university staff (USTF) and Preschool Students Per 100,000 Population (PSPH). Environmental governance and pollutant emission variables included Industrial Pollution Treatment Investment (IPTI), Environmental Emergencies (ENVE), NOx Emissions (NOXE), Particulate Matter Emissions (PME), Wastewater Treatment Investment (WWTI), COD Emissions (CODE), and Local Environmental Protection

Expenditure (LEPE). Technological innovation variables included Domestic Patent Applications (DPA) and Technology Market Turnover (TMT). Variable definitions are shown in Table 1.

Table 2 presents descriptive statistics for all variables. The mean TOV was 17.82, with a standard deviation of 23.06. The minimum was 0.00, and the maximum was 181.00. This indicates clear differences in tuberculosis outpatient visits across provinces and years. GDPPC and DIPC showed large standard deviations, suggesting substantial regional differences in economic development and income. For health resources, the distributions of HTTP and HBED indicate uneven health service supply across regions. Education resources, environmental governance, pollutant emissions, technological innovation, and technology market variables also showed substantial dispersion. These differences reflect clear heterogeneity in socioeconomic conditions, public services, and environmental conditions. This heterogeneity provides a basis for analyzing regional differences and related predictors of TOV.

Table 1. Variable definitions.

Variable	Unit	Definition
TOV	10 ⁴ visits	Tuberculosis outpatient visits
GDPPC	CNY per capita	GDP per capita
DIPC	CNY per capita	Disposable income per capita
HTTP	persons per 10,000 population	Health technicians per 10,000 population
HBED	10 ⁴ beds	Hospital beds
USTF	10 ⁴ persons	University staff
PSPH	students per 100,000 population	Preschool students per 100,000 population
IPTI	10 ⁴ CNY	Industrial pollution treatment investment
ENVE	events	Environmental emergencies
NOXE	10 ⁴ tonnes	NOx emissions
PME	10 ⁴ tonnes	Particulate matter emissions
DPA	items	Domestic patent applications
WWTI	10 ⁴ CNY	Wastewater treatment investment
CODE	10 ⁴ tonnes	COD emissions
LEPE	10 ⁸ CNY	Local environmental protection expenditure
TMT	10 ⁸ CNY	Technology market turnover

Table 2. Descriptive statistics.

Variable	Mean	Std	Min	Q1	Median	Q3	Max
TOV	17.82	23.06	0.00	4.85	12.20	22.83	181.00
GDPPC	66873.23	35993.58	19188.00	42126.00	56999.50	77034.00	228167.00
DIPC	28630.41	13828.59	9768.00	19002.75	25867.00	32980.75	88366.00
HTTP	71.65	18.42	36.00	58.00	70.00	83.00	155.00
HBED	27.15	17.33	2.60	15.03	23.21	36.95	77.74
USTF	8.53	4.77	0.62	4.92	7.72	11.72	21.45
PSPH	3012.98	834.75	998.00	2439.50	3088.00	3538.50	6371.00
IPTI	199763.75	200129.89	476.00	69554.75	136104.50	264330.00	1416464.00
ENVE	10.34	20.63	0.00	2.00	6.00	11.00	251.00
NOXE	47.56	34.99	3.49	23.07	38.73	60.77	176.11
PME	34.55	30.43	0.41	10.98	26.56	50.03	179.77
DPA	128634.79	175587.37	844.00	28085.25	62928.00	156026.50	1004280.00
WWTI	28404.18	34789.97	15.00	5468.75	15862.50	37026.75	263797.00
CODE	63.99	51.97	1.97	19.55	49.39	105.21	192.12
LEPE	161.39	99.02	21.23	95.02	140.42	209.31	747.44
TMT	839.35	1434.16	0.57	51.92	218.21	871.00	9153.26

Results

Temporal Trends and Interprovincial Distribution of tuberculosis outpatient visits

Temporal trend of tuberculosis outpatient visits

Figure 2 shows the temporal trend of TOV from 2012 to 2024. Overall, the median TOV across the 30 provinces increased from 8.65×10^4 visits in 2012 to 13.90×10^4 visits in 2024. This suggests a general increase in tuberculosis outpatient visits during the study period. The trend may be related to improved case detection, better access to care, stronger health awareness, and continued development of tuberculosis control systems. The yearly distributions also show clear regional differences. From 2012 to 2015, the

boxplots were relatively narrow, and the median TOV remained low. This suggests that interprovincial differences were relatively small in the early years. After 2016, the interquartile ranges became wider, and the upper quartiles increased in some years. This indicates that outpatient service use increased in some regions. High-value outliers appeared in every year, suggesting that some provinces had much higher outpatient visit volumes in certain years. Overall, the temporal change in TOV was not a simple linear increase. It showed a slow upward trend, annual fluctuation, and local high-value patterns. These patterns may be associated with regional health resources, population mobility, case detection capacity, and public health management.

Interprovincial distribution of tuberculosis outpatient visits

Figure 3 shows differences in TOV across provinces. Overall, TOV was highly uneven across provinces. Median values,

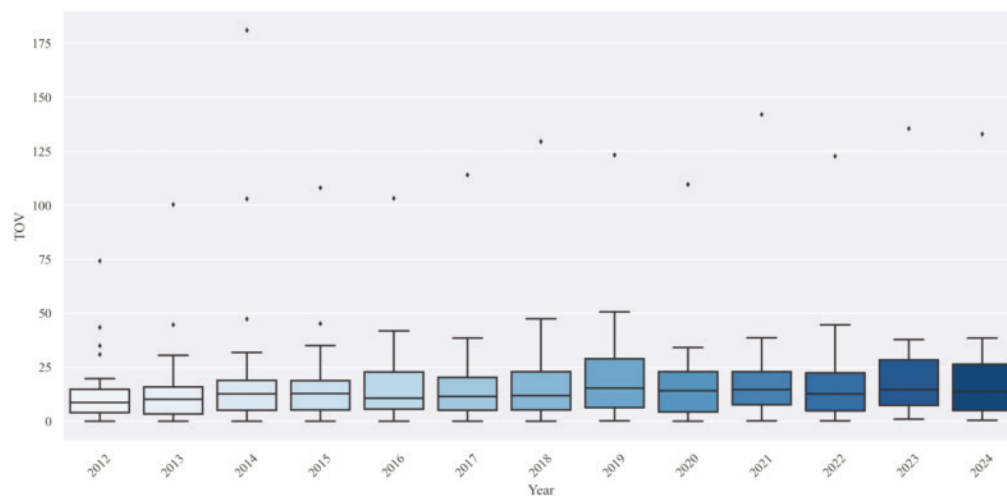


Figure 2. Temporal trend of tuberculosis outpatient visits.

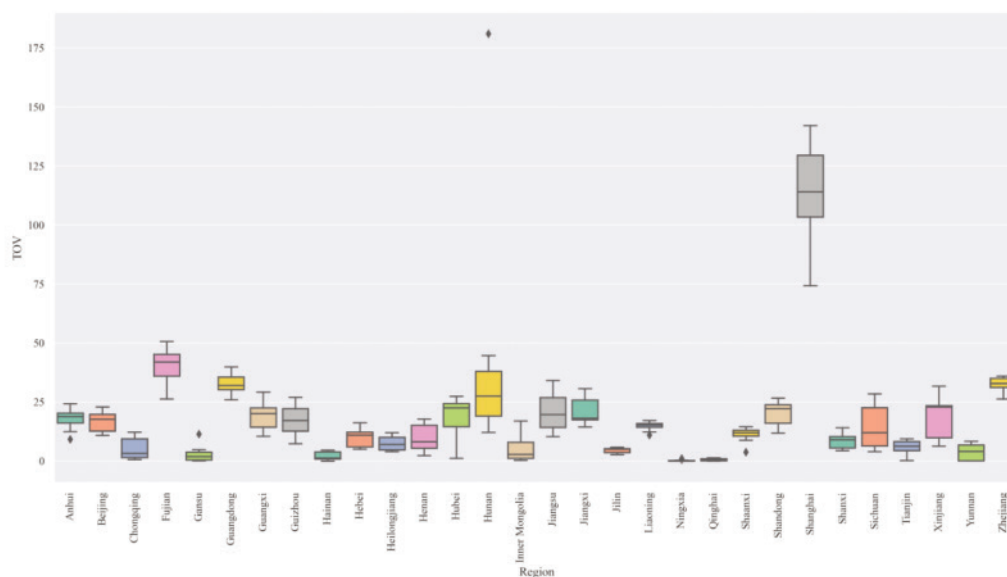


Figure 3. Interprovincial distribution of tuberculosis outpatient visits.

interquartile ranges, and outliers varied widely. Shanghai had a substantially higher total recorded outpatient volume than other provinces. Its median was about 1.14 million visits, and most values were between 1.00 and 1.30 million visits. This suggests a high level of tuberculosis outpatient service use. It is important to note that a higher total recorded outpatient volume does not necessarily indicate a higher tuberculosis incidence risk. It may reflect stronger service absorption capacity, better case detection, larger population mobility, and a regional concentration of diagnostic services. Fujian, Guangdong, and Zhejiang also had relatively higher total recorded outpatient volumes. The median for Fujian was about 400,000 visits, while Guangdong and Zhejiang both had medians above 300,000 visits. These patterns may be related to higher economic development, more concentrated health resources, larger migrant populations, and better access to care. In contrast, Hainan, Ningxia, Qinghai, Inner Mongolia, and Yunnan had lower total recorded outpatient volumes, with most medians below 50,000 visits. These lower values may be related to population size, service use, case detection capacity, and regional health resource allocation. Hunan, Sichuan, and Xinjiang showed wider boxplots, indicating larger annual fluctuations. Overall, TOV displayed marked geographical heterogeneity across provinces. Higher values were concentrated mainly in the eastern coastal provinces of Shanghai, Fujian, Guangdong, and Zhejiang, whereas lower values were observed in Hainan, Ningxia, Qinghai, Inner Mongolia, and Yunnan. Hunan, Sichuan, and Xinjiang also showed greater year-to-year variation than most other provinces. This distribution may reflect regional differences in population size, population mobility, economic development, health-resource concentration, and access to outpatient services.

Correlation analysis

Figure 4 presents the correlation matrix. Overall, TOV had the strongest correlations with economic variables. DIPC and GDPPC showed moderate positive correlations with TOV, with correlation coefficients of 0.52 and 0.50, respectively. This suggests that provinces with higher economic development tend to have higher total recorded outpatient volumes. This may be related to better access to care, greater payment capacity, and stronger case detection. Among technological innovation variables, DPA and TMT showed weak positive correlations with TOV, with coefficients of 0.27 and 0.24, respectively. This suggests that innovation capacity and technology transfer may be indirectly associated with tuberculosis outpatient service utilization. Among health and education variables, USTF, HTTP, and HBED had weaker correlations with TOV, with coefficients of 0.22, 0.14, and 0.11, respectively. Among environmental variables, ENVE, WWTI, and LEPE showed weak positive correlations with TOV, while NOXE and PME showed weak negative correlations. These results suggest

that the relationship between environmental factors and TOV may be more complex and nonlinear.

Some predictors were also correlated with each other. For example, the correlation between GDPPC and DIPC was 0.97. The correlation between HBED and USTF was 0.83, and that between NOXE and PME was 0.69. Although these variables were retained because they represent conceptually distinct dimensions, their correlations should be considered when interpreting the importance assigned to individual predictors. These correlations suggest that some variables may jointly reflect regional economic development, resource allocation, or pollutant emissions. Correlation analysis can only capture linear relationships. It cannot identify nonlinear relationships, threshold effects, or interactions. Therefore, XGBoost-SHAP was used for further analysis of the related predictors of TOV.

Comparison of model predictive performance

To compare model fitting and prediction, seven models were constructed: XGBoost, random forest, linear regression, ridge regression, gradient boosting, KNN, and lasso regression. Model performance was evaluated using R², RMSE, MAE, and MSE. Table 3 shows the comparison results. XGBoost performed best among all candidate models, with an R² of 0.8154, RMSE of 8.8056, MAE of 5.3717, and MSE of 77.5387. In the additional five-fold cross-validation conducted within the training set, XGBoost achieved a mean R² of 0.595 (SD = 0.187), a mean RMSE of 14.584 (SD = 6.408), and a mean MAE of 7.191 (SD = 1.041). The variation across folds suggests that predictive performance was sensitive to sample composition, potentially reflecting the substantial heterogeneity in provincial TOV. In the sensitivity analysis, adding Year as a predictor did not improve model performance. The year-inclusive model yielded an R² of 0.734, an RMSE of 10.578, and an MAE of 5.926 on the independent test set. Year had a feature importance score of 0.010 and ranked 15th among the 16 predictors, indicating that it provided limited additional predictive information beyond the variables included in the primary model. Random forest ranked second, with an R² of 0.7694 and RMSE of 9.8433. Linear regression and ridge regression had R² values of 0.7491 and 0.7481, respectively. These results suggest that linear models can explain part of the variation in TOV, but they are less effective than ensemble models in capturing complex nonlinear relationships.

Overall, XGBoost achieved a higher R² and lower error values than the other models. This suggests that it captured complex associations between TOV and multidimensional related factors more effectively. Therefore, XGBoost was used as the main predictive model in the subsequent analysis. SHAP was then used to explain each variable’s contribution to model predictions.

Table 3. Model performance comparison.

Model	R ²	RMSE	MAE	MSE
XGBoost	0.8154	8.8056	5.3717	77.5387
Random forest	0.7694	9.8433	5.7142	96.8907
Linear regression	0.7491	10.2670	7.8444	105.4103
Ridge	0.7481	10.2878	7.8206	105.8392
Gradient boosting	0.7088	11.0601	6.5184	122.3265
KNN	0.6950	11.3193	6.9836	128.1259
Lasso	0.6182	12.6650	8.5256	160.4024

XGBoost results

Feature importance results from the XGBoost model are shown in Figure 5. DIPC, USTF, and DPA made relatively large contributions to the prediction of TOV, with feature importance scores of about 0.29, 0.21, and 0.09. These results indicate that income, education resources, and regional innovation capacity were important predictors identified by the model. The high importance of DIPC may be related to payment capacity, service use, and active health-seeking behavior. USTF may reflect regional education resources and health knowledge dissemination. DPA may reflect regional innovation capacity, medical technology diffusion, and public service modernization.

HBED and TMT also showed some importance, with scores of about 0.07. This suggests that health service capacity and technolo-

gy market activity may be associated with tuberculosis outpatient service utilization. In contrast, environmental governance and pollutant emission variables, including ENVE, WWTI, LEPE, CODE, NOXE, PME, and IPTI, had lower feature importance values, all below 0.04. This does not mean that environmental factors have no public health relevance. Rather, it indicates that their overall contribution to TOV prediction was relatively small in the current model. Although their overall importance was low, the later SHAP dependence plots show that some environmental variables still had nonlinear predictive contributions within specific value ranges. XGBoost feature importance reflects relative contribution in model prediction. It does not represent causal effects in an epidemiological sense. Therefore, SHAP was used for further analysis of the direction and nonlinear patterns of each variable's contribution.

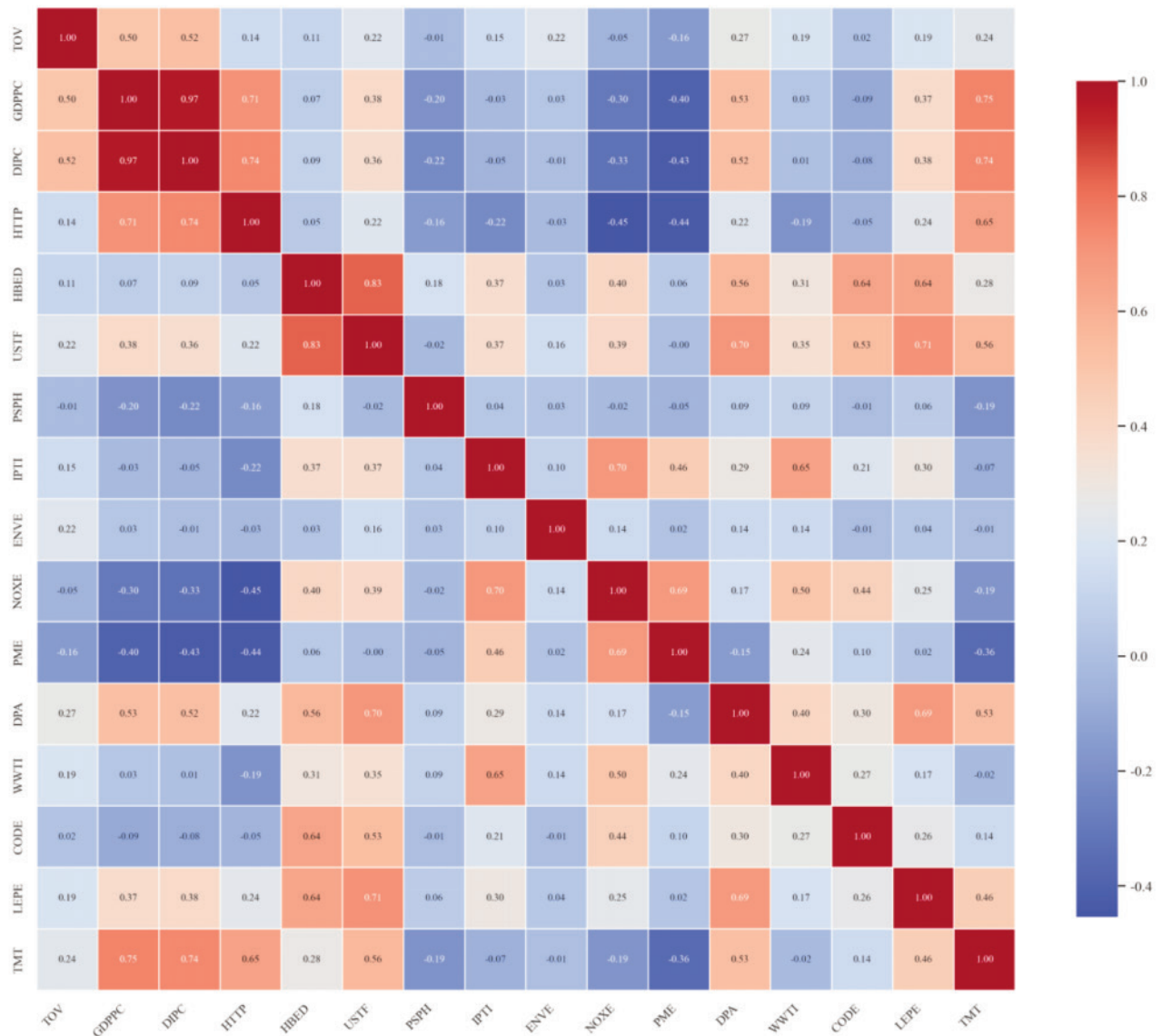


Figure 4. Correlation matrix.

SHAP results

Figure 6 presents the SHAP summary plot. It shows the direction and magnitude of each variable’s contribution to the XGBoost prediction of TOV. Overall, DIPC had the widest SHAP value distribution. This indicates that it contributed the most to TOV prediction. Higher DIPC values were usually associated with higher positive SHAP values. This suggests that provinces with higher disposable income per capita tended to have higher predicted TOV. GDPPC and USTF also showed relatively clear positive contributions. This suggests that economic development and education resources may have predictive associations with tuberculosis outpatient service utilization. HTTP and HBED showed more complex nonlinear patterns. This suggests that health resource vari-

ables were not linearly associated with predicted TOV, and their contributions may depend on resource allocation and regional differences. Among environmental and technological innovation variables, DPA, WWTI, CODE, NOXE, PME, LEPE, and TMT had relatively concentrated SHAP value distributions. However, some variables changed direction across different value ranges. This suggests possible threshold effects or stage-specific patterns in their associations with predicted TOV. Overall, SHAP analysis indicates that interprovincial differences in TOV cannot be explained by a single factor. They are jointly associated with economic development, income, health resources, education resources, environmental governance, and technological innovation. Figure 7 presents SHAP dependence plots for the eight predictors discussed in the main text. To improve the readability of the

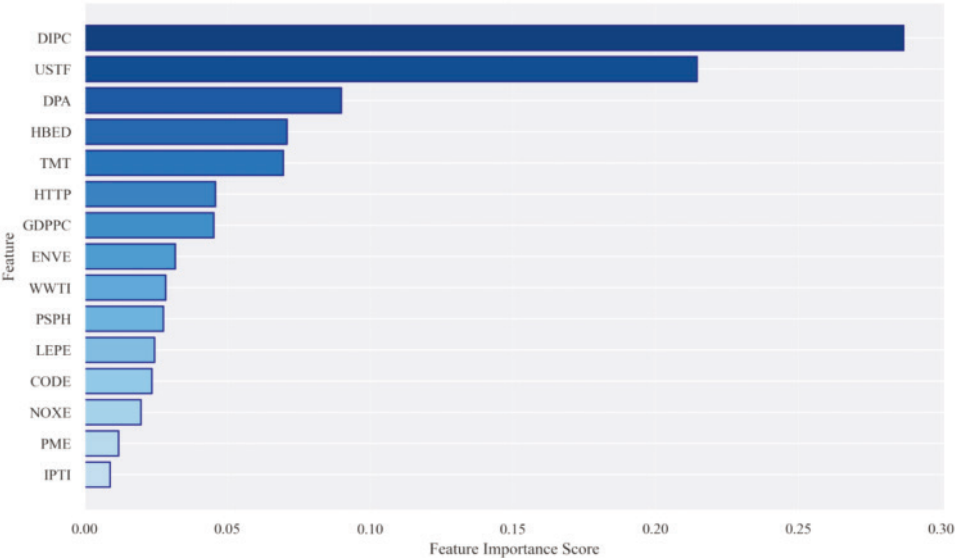


Figure 5. XGBoost feature importance ranking.

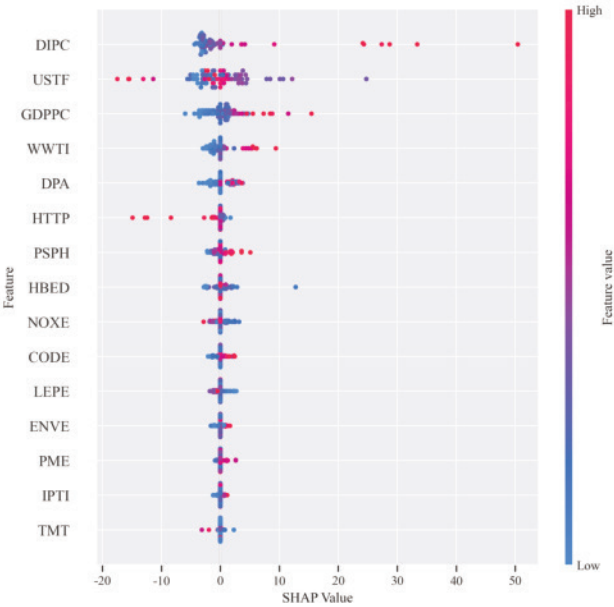


Figure 6. SHAP summary plot.

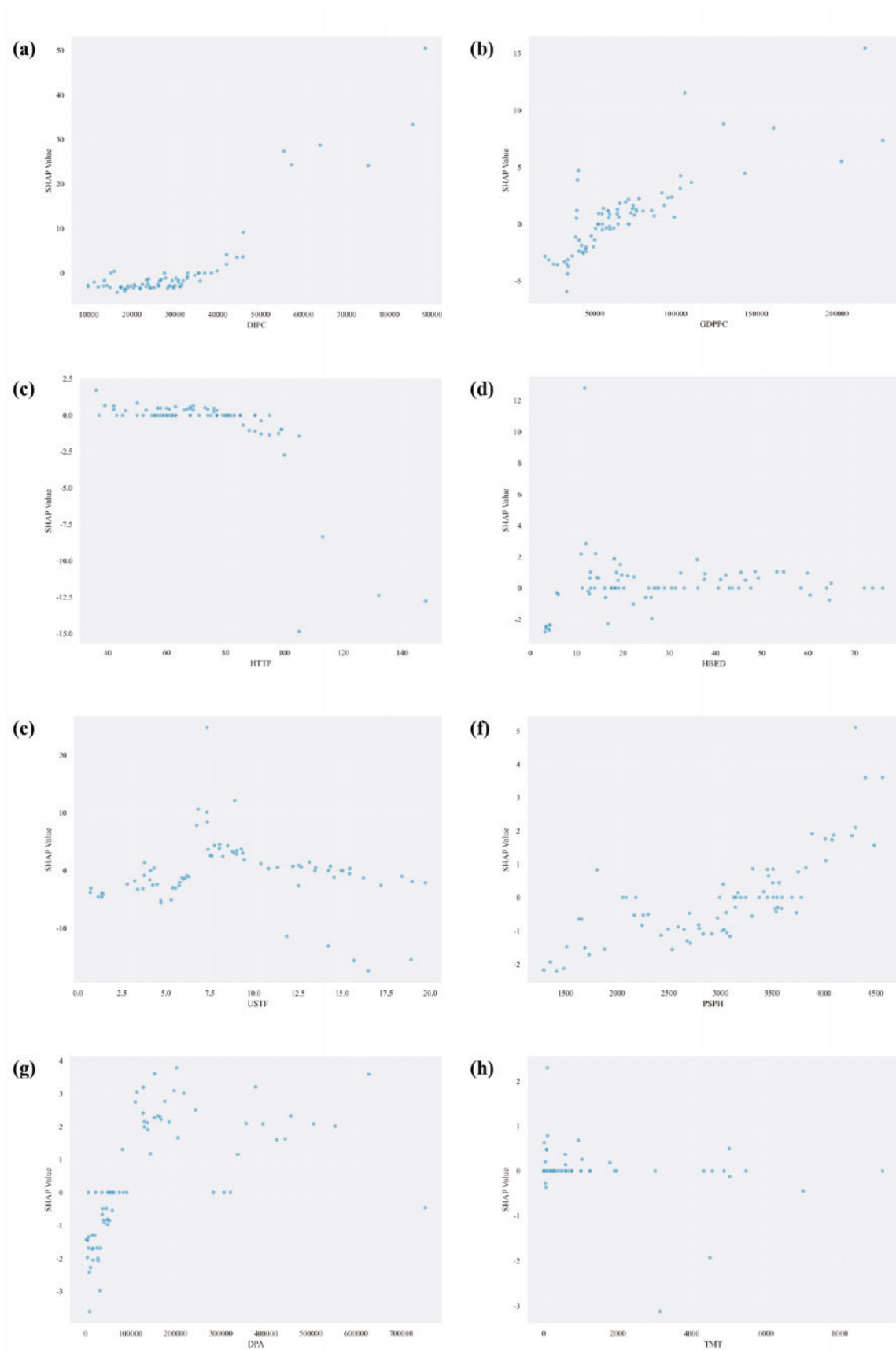


Figure 7. SHAP dependence plots for the principal predictors of TOV: (a) DIPC, (b) GDPPC, (c) HTTP, (d) HBED, (e) USTF, (f) PSPH, (g) DPA, and (h) TMT.

main figure, the corresponding plots for environmental governance and pollutant-emission variables with lower model-derived importance are presented in Figure 8.

SHAP-based association between disposable income per capita and predicted tuberculosis outpatient visits

Figure 7(a) shows the nonlinear relationship between DIPC and TOV. Overall, DIPC had a nonlinear positive association with predicted TOV. When DIPC was below about 35,000 CNY per capita, SHAP values mostly fluctuated around zero. This suggests that DIPC contributed little to TOV prediction in lower-income regions. When DIPC exceeded about 35,000 CNY per capita, SHAP values gradually became positive. This indicates that higher DIPC was associated with higher predicted TOV in the model. When DIPC exceeded about 45,000 CNY per capita, positive SHAP values increased further. This may reflect stronger payment capacity, health awareness, and active health-seeking behavior in higher-income regions.

SHAP-based association between GDP per capita and predicted tuberculosis outpatient visits

Figure 7(b) shows the nonlinear relationship between GDPPC and TOV. Overall, GDPPC showed a pattern that shifted from negative to positive and then gradually strengthened. When GDPPC was below about 45,000 CNY per capita, SHAP values were mostly negative. This suggests that the economic base contributed weakly, and sometimes negatively, to predicted TOV in less developed regions. This may be related to limited primary health resources, lower public health investment, and weaker care-seeking capacity. When GDPPC ranged from about 45,000 to 90,000 CNY per capita, SHAP values moved toward zero. This may reflect better public health investment, health insurance coverage, and service accessibility in more developed regions. When GDPPC exceeded about 90,000 CNY per capita, SHAP values became clearly positive. This suggests that higher GDPPC was associated with higher predicted TOV, possibly reflecting stronger service supply and case detection capacity.

SHAP-based association between health technicians per 10,000 population and predicted tuberculosis outpatient visits

Figure 7(c) shows the nonlinear relationship between HTTP and TOV. HTTP had a clear stage-specific contribution. When HTTP was below about 35 persons per 10,000 population, SHAP values were positive or increased gradually. This suggests that an increase in HTTP may be associated with higher predicted TOV in regions with relatively insufficient health workers. It may reflect differences in case detection, diagnosis, treatment, and follow-up capacity. When HTTP ranged from about 35 to 85 persons per 10,000 population, SHAP values were mostly close to zero. This suggests that the marginal contribution stabilized after health worker supply reached a certain level. When HTTP exceeded about 85 persons per 10,000 population, some SHAP values became negative. This suggests that a higher density of health workers does not necessarily correspond to a higher predicted TOV. It may reflect differences in the spatial distribution of health workers, the concentration of high-quality resources, and the allocation of primary tuberculosis control personnel.

SHAP-based association between hospital beds and predicted tuberculosis outpatient visits

Figure 7(d) shows the nonlinear relationship between HBED and TOV. The relationship was not simply linear. It showed stage-

specific changes. When HBED was below about 80,000 beds, SHAP values were mostly negative. This suggests that lower HBED was associated with lower predicted TOV in the model. It may reflect the relationship between bed resources and the service capacity of tuberculosis diagnosis and treatment. When HBED ranged from about 80,000 to 180,000 beds, SHAP values became positive and reached higher levels. This suggests that a moderate supply of bed resources may be associated with higher predicted TOV. It may reflect differences in service accessibility and outpatient-referral coordination. When HBED increased further, SHAP values gradually declined. Some high-bed regions even showed negative contributions. This suggests that a larger number of beds does not necessarily increase tuberculosis outpatient service utilization. The key issue may be whether bed resources match primary care, specialized tuberculosis services, and regional population needs.

SHAP-based association between university staff and predicted tuberculosis outpatient visits

Figure 7(e) shows the nonlinear relationship between USTF and TOV. USTF generally followed an inverted U-shaped pattern. When USTF was below about 65,000 persons, SHAP values were mostly negative or close to zero. This suggests that USTF contributed little to TOV prediction in regions with fewer university staff. When USTF ranged from about 65,000 to 90,000 persons, SHAP values increased clearly. This suggests that a moderate concentration of higher education resources may be associated with health knowledge dissemination, public health workforce training, and regional service capacity. When USTF exceeded about 90,000 persons, SHAP values declined, and some samples became negative. This may be related to the over-concentration of education and health resources in core cities. It may also reflect a mismatch between resource concentration and primary service accessibility.

SHAP-based association between preschool students per 100,000 population and predicted tuberculosis outpatient visits

Figure 7(f) shows the nonlinear relationship between PSPH and TOV. PSPH showed a gradual shift from negative to positive. When PSPH was below about 2,000 students per 100,000 population, SHAP values were mostly negative. This suggests that regions with fewer preschool students may also have weaker public service foundations, limited family health management, and insufficient primary public health services. When PSPH ranged from about 2,000 to 3,000 students per 100,000 population, SHAP values gradually moved toward zero. This may reflect better child health management and stronger family health awareness in regions with stronger preschool education resources. When PSPH exceeded about 3,000 students per 100,000 population, SHAP values were mostly positive. This may reflect stronger child health management, family health awareness, and primary public service capacity in regions with better education resources. PSPH does not directly represent tuberculosis screening. It should be interpreted as a proxy for regional education and public service development.

Nonlinear predictive contributions of environmental governance and pollutant emission variables

Figure 8 shows the SHAP-based associations between environmental governance and pollutant-emission predictors and predicted TOV. Compared with DIPC, USTF, DPA, HBED, and TMT, these variables had lower overall feature importance. This suggests that their overall contribution to model prediction was limited. However, the SHAP dependence plots show that some environ-

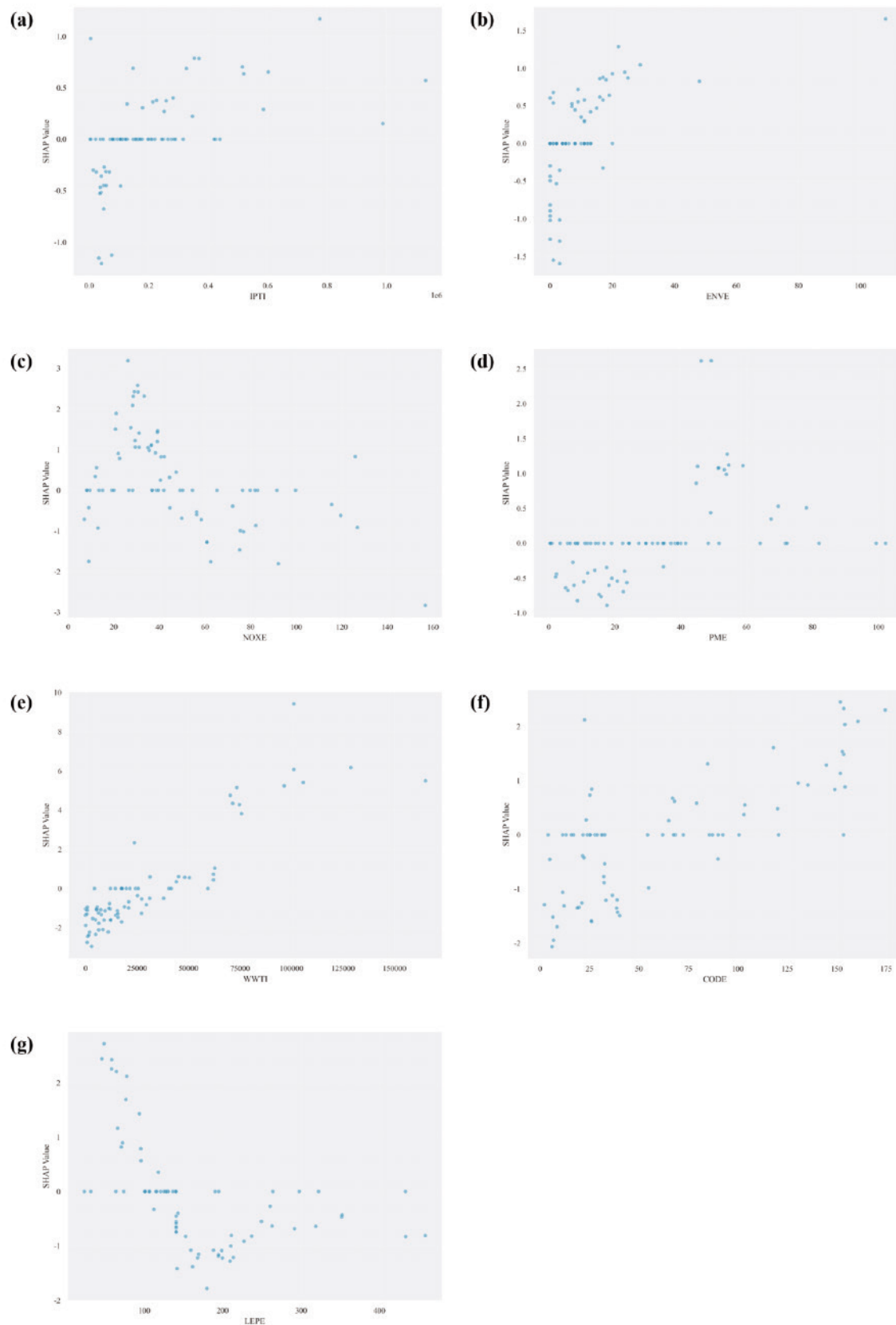


Figure 8. SHAP dependence plots for environmental governance and pollutant-emission predictors with lower model-derived importance: (a) IPTI, (b) ENVE, (c) NOXE, (d) PME, (e) WWTI, (f) CODE, and (g) LEPE.

mental variables still had nonlinear predictive contributions in different value ranges. This suggests stage-specific or threshold-type associations between environmental factors and predicted TOV. For environmental governance investment, IPTI and WWTI generally shifted from negative to positive contributions. When industrial pollution treatment investment or wastewater treatment investment was low, SHAP values were mostly negative or close to zero. This suggests that these variables contributed little to predicted TOV in low-investment regions. As investment increased, SHAP values moved toward zero and became positive in some higher-value ranges. This may reflect stronger fiscal capacity, local governance capacity, and public service conditions in regions with higher environmental governance investment. LEPE showed an inverted U-shaped pattern. Moderate local environmental protection expenditure was associated with higher predicted TOV, while SHAP values declined at higher levels of expenditure. This suggests that LEPE was not linearly associated with predicted TOV. Its contribution may be affected by investment structure, fiscal resource allocation, and the efficiency of converting environmental spending into health service benefits. For pollutant emissions, NOXE, PME, and CODE showed different SHAP patterns. NOXE generally showed a rise-and-fall pattern, suggesting a complex stage-specific association with predicted TOV. PME and CODE were mostly negative or close to zero at lower values, but SHAP values became positive at higher values. This may reflect the combined association of pollution exposure risk, industrialization, health service demand, and disease surveillance capacity. These findings do not indicate that pollutant emissions directly increase or decrease tuberculosis outpatient visits. They only show nonlinear predictive relationships between pollutant emission variables and predicted TOV in the model. ENVE also showed a shift from weak contribution to positive contribution. When environmental emergencies were rare, the contribution to predicted TOV was small. At higher values, ENVE showed larger positive SHAP values. This may reflect differences in environmental health risk exposure, public health surveillance needs, and case detection capacity in regions with more environmental emergencies. Overall, environmental governance and pollutant emission variables were not the main predictors in the model. Still, their SHAP dependence relationships suggest that environmental factors may be nonlinearly associated with predicted TOV through local governance capacity, public service conditions, environmental health risk, and health service utilization.

SHAP-based association between domestic patent applications and predicted tuberculosis outpatient visits

Figure 7(g) shows the nonlinear relationship between DPA and TOV. DPA showed stage-specific changes. When DPA was below about 100,000 items, SHAP values were mostly negative. This suggests that DPA contributed little to predicted TOV in regions with weaker innovation capacity or where innovation resources had not been effectively translated into health service capacity. When DPA ranged from about 100,000 to 300,000 items, SHAP values gradually moved toward zero. This may reflect advantages in medical technology diffusion and public service modernization in regions with more innovation activity. When DPA exceeded about 300,000 items, SHAP values generally became positive. This suggests that higher DPA was associated with higher predicted TOV, possibly reflecting differences in medical technology supply, disease surveillance capacity, and health service systems. However, DPA is a proxy for regional innovation capacity. It does not directly represent tuberculosis-related patents or medical innovation.

SHAP-based association between technology market turnover and predicted tuberculosis outpatient visits

Figure 7(h) shows the nonlinear relationship between TMT and TOV. TMT showed a segmented nonlinear pattern. When TMT was below about 100 billion CNY, SHAP values were generally positive. This may reflect an association between moderate technology market activity, medical technology diffusion, and improved primary service capacity. When TMT ranged from about 100 to 350 billion CNY, SHAP values declined sharply and became negative. This suggests that technology market expansion is not simply associated with higher predicted TOV. It may reflect differences in the allocation of technology resources, the degree of health sector translation, and regional resource matching. When TMT exceeded about 350 billion CNY, SHAP values gradually converged toward zero. This may reflect a mismatch between high-end technology development and equitable public health services in regions with highly active technology markets. Overall, TMT had a complex nonlinear association with predicted TOV. The key issue is not the scale of technology transactions itself, but whether technological outputs can be translated into primary diagnosis and treatment, disease surveillance, and public health management capacity.

Discussion

Using panel data from 30 Chinese provinces from 2012 to 2024, this study applied XGBoost-SHAP to examine temporal trends, interprovincial differences, and related predictors of TOV. The results show that TOV increased slowly over the study period and differed clearly across provinces. This finding is indirectly consistent with Guo *et al.* (2025), who identified spatiotemporal clustering in pulmonary tuberculosis incidence in China. However, the provinces with higher total recorded outpatient volumes identified in this study, including Shanghai, Fujian, and Guangdong, were not necessarily those with the highest reported tuberculosis incidence. This distinction further indicates that TOV reflects service utilization and case-detection capacity rather than population-level incidence or disease burden alone. X. Chen *et al.* (2024) also noted that tuberculosis service management in primary care, including patient tracking and case management, was better in eastern China than in western China. This may partly explain the higher total recorded outpatient volumes in eastern provinces.

The model comparison showed that XGBoost had the best predictive performance among all candidate models ($R^2 = 0.8154$). This suggests that TOV is associated with complex nonlinear patterns across multiple regional factors. This finding is consistent with Tao *et al.* (2026), who showed that machine learning can identify nonlinear relationships in tuberculosis-related outcomes. SHAP analysis further showed that DIPIC had the largest SHAP-based contribution to model predictions. When DIPIC exceeded about 35,000 CNY, SHAP values became positive. When DIPIC exceeded 45,000 CNY, positive SHAP values increased further. This result aligns with Wu *et al.* (2023), who discussed the relationship between socioeconomic vulnerability and tuberculosis risk. It is also consistent with Ferreira *et al.* (2023), who emphasized the importance of social protection in tuberculosis control. In lower-income regions, limited payment capacity and lower health awareness may reduce service use and increase diagnostic delay. This is consistent with studies of care-seeking and diagnostic delay among tuberculosis patients (L. Zhang *et al.*, 2024; Fan *et al.*, 2025).

The SHAP-based associations of HTTP and HBED with predicted TOV were nonlinear. This suggests that more health resources do not automatically correspond to higher tuberculosis outpatient service use. Resource allocation and primary care accessibility may be more important. X. Chen *et al.* (2024) also reported regional differences in the role of primary care in tuberculosis control. Patient tracking and case management were weaker in western regions. R. Sun *et al.* (2024) found that migrants, women, and older adults in Shanghai had longer patient delays. Some industrial areas also had a high risk of health system delay. These findings suggest that barriers to service use may remain even in regions with relatively strong health resources.

Environmental governance and pollutant emission variables had relatively low overall importance, but they still showed nonlinear predictive contributions in some value ranges. This finding is broadly consistent with the meta-analysis by Dimala and Kadia (2022), which examined the association between air pollution exposure and pulmonary tuberculosis risk. Ma *et al.* (2026) also reported spatial inequalities in the tuberculosis burden attributable to long-term particulate matter exposure. However, those studies mainly focused on tuberculosis risk or disease burden, while the outcome in this study was TOV. Therefore, environmental variables should be interpreted as nonlinear predictive associations among environmental governance, pollution exposure, public service capacity, and outpatient service use. They should not be interpreted as direct causal effects on TOV.

For technological innovation, DPA became positively associated with predicted TOV after about 100,000 applications. TMT showed a positive-negative-flat pattern. These findings are broadly consistent with Tao *et al.* (2026), who showed that multidimensional socioeconomic and environmental variables can support tuberculosis-related prediction. Peng *et al.* (2024) and J. Chen *et al.* (2024) also showed that machine learning can be used to predict treatment failure and loss to follow-up among tuberculosis patients. This suggests that information technology and technical capacity may have value for tuberculosis management. However, the SHAP-based contributions of DPA and TMT to model predictions were moderate in this study. This may indicate that patents and technology market outputs have not yet been fully translated into primary tuberculosis control and outpatient service utilization.

This study has several limitations. First, TOV represents total outpatient service volume rather than unique patients or population-standardized visit rates. Provincial differences in TOV may therefore reflect population size, healthcare-seeking behavior, service accessibility, case-detection capacity, and underlying disease burden, and should not be interpreted as differences in tuberculosis incidence. Second, several predictors were highly correlated, particularly GDPPC with DIPC and HBED with USTF. Although XGBoost is relatively robust to multicollinearity, correlated predictors may share or redistribute SHAP values, potentially affecting their individual importance rankings. Therefore, the SHAP values of correlated predictors should be interpreted jointly within the full model, rather than as separate contributions from individual variables. Finally, although the sensitivity analysis indicated limited additional predictive value of Year, the pooled design did not explicitly account for within-province temporal dependence or lagged associations; these temporal dynamics should be examined in future longitudinal studies.

Conclusions

This study used panel data from 30 Chinese provinces from

2012 to 2024. It examined TOV using correlation analysis, model comparison, and XGBoost-SHAP. The study analyzed temporal trends, interprovincial differences, and related predictors of TOV. It shifts the perspective from disease burden alone to tuberculosis-related outpatient service utilization. It also provides evidence for identifying nonlinear predictive associations between regional factors and TOV. Because TOV represents total recorded outpatient service volume rather than a population-standardized incidence measure, provincial differences in TOV should not be interpreted as differences in tuberculosis incidence.

The model-derived thresholds should be treated as signals for local service assessment rather than as universal intervention cut-offs. In provinces with DIPC below approximately 35,000 CNY per capita and lower total recorded outpatient volumes, health authorities should first assess whether financial barriers contribute to insufficient service utilization. Where such barriers are identified, targeted measures may include strengthening reimbursement for tuberculosis outpatient care, providing transportation support, and improving community-based referral. Provinces with fewer than approximately 35 health technicians per 10,000 population should assess shortages of tuberculosis-trained primary care personnel and prioritize targeted workforce training, retention, and diagnostic-referral coordination. In provinces with higher total recorded outpatient volumes, clinic staffing, laboratory capacity, referral, and follow-up services should be aligned with the observed service workload. The nonlinear association with HBED further suggests that simply increasing bed numbers may be less useful than strengthening coordination between hospital beds, primary care, and specialized tuberculosis services. These actions should be guided by local population size, notified tuberculosis incidence, and healthcare-access data, rather than by TOV alone.

Future studies should consider population-standardized TOV, notified tuberculosis incidence, spatial autocorrelation models, lagged variables, and county-level or individual-level data. These extensions may help explain regional differences in tuberculosis outpatient service utilization more accurately.

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