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Original Research Article

Predicting Patient Satisfaction in Indian Healthcare Using Artificial Intelligence: A Data-Driven Approach to Patient Relationship Management

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ABSTRACT

Background: Patient satisfaction serves as a vital measure of healthcare quality, especially in regions with limited resources, such as Chhattisgarh, India—a state characterized by its tribal populations and underdeveloped medical infrastructure. This research employs Artificial Intelligence (AI) to forecast patient satisfaction levels, specifically the overall satisfaction, with the goal of improving patient relationship management (PRM) in a public hospital setting in Chhattisgarh. **Methods:** Data from 107 patient surveys were examined, encompassing demographic factors (e.g., age group, gender, income level, and frequency of visits), service quality aspects (e.g., timeliness, accessibility, communication, system efficiency), and views on technology (e.g., technology quality and usability). An XGBoost regression model was developed to predict the overall satisfaction, complemented by SHapley Additive exPlanations (SHAP) for model interpretability. Additional analyses involved Pearson correlations, multiple linear regression, and *t*-tests. Missing values (under 5%) were handled through *k*-Nearest Neighbors (*k*-NN) imputation. The study did not involve preregistration or animal testing. **Results:** The XGBoost model yielded a root mean squared error (RMSE) of 0.39 and a coefficient of determination, R^2 of 0.90. SHAP highlighted communication (mean SHAP value = 0.72, $p < 0.001$), system efficiency (0.48, $p < 0.01$), and technology usability (0.35, $p < 0.05$) as primary influencers. Correlations revealed strong links, such as between communication and the overall satisfaction (correlation coefficient, r = 0.82, $p < 0.001$). Regression analysis supported the significance of communication ($\beta = 0.70$, $p < 0.001$) and system efficiency ($\beta = 0.45$, $p < 0.01$). Patients with very frequent visits showed reduced satisfaction (mean = 3.5 vs. 4.0 for occasional visitors, $p < 0.001$). **Conclusions:** Artificial Intelligence demonstrates strong potential for predicting patient satisfaction, emphasizing the roles of communication and operational efficiency. These insights could guide targeted PRM interventions in Chhattisgarh to better serve tribal and low-income groups. However, given the modest sample size from a single site, results should be viewed as preliminary, warranting larger-scale validation.

Keywords—*Patient satisfaction, Artificial intelligence, Predictive analytics, Healthcare technology, SHAP, Patient relationship management.*

INTRODUCTION

Patient satisfaction, defined here as the overall satisfaction (OS), captures how well healthcare services meet patient expectations, influencing treatment adherence, trust in providers, and long-term health results.[1] In India, with its population surpassing 1.4 billion, public health systems grapple with resource shortages and varied patient demands.[2] This challenge is amplified in Chhattisgarh, a central state home to 29.4 million people, including 30.6% from tribal groups in remote areas.[3] The state's healthcare faces constraints, with just 1.8 beds per 1000 residents (below India's average of 2.9 beds) and a doctor–patient ratio of 1:2000, falling short of the World Health Organization's 1:1000 standard.[4] Effective patient relationship management (PRM) is essential to elevate patient experiences and streamline care in such environments.[5]

Conventional methods for gauging satisfaction, such as paper surveys, are typically conducted after the fact, leading to issues such as recall inaccuracies and delayed insights. For instance, research in Indian public hospitals indicates that 60% of surveys occur post-discharge, limiting their use for immediate improvements.[6] Artificial intelligence (AI) presents a forward-looking alternative by forecasting OS in real time using diverse data sources, enabling timely PRM adjustments.[7] In Chhattisgarh, where 70% of surveyed patients were women and 40% earn Indian rupees (Rs.) 10,000–20,000 monthly, AI can tailor solutions to address needs such as accessible communication and user-friendly technology for tribal and economically disadvantaged communities.[8]

This investigation draws on 107 patient surveys collected in April 2025 from a Chhattisgarh public hospital. OS averaged 3.85 (standard deviation [SD] = 0.92) on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). [9] The data covered the following:

- **Demographics:** Age group (60% aged 25–34 years), gender, income level, and visit frequency (35% occasional).[10]
- **Service quality:** Timeliness (mean = 3.75, SD = 0.95), accessibility (3.80, 0.90), communication (4.15, 0.75), and system efficiency (4.05, 0.80).[11]
- **Satisfaction metrics:** OS, expectations met, feeling valued, and communication satisfaction.[12]
- **Technology aspects:** Technology quality, usability (3.90, 0.85), communication via technology, and efficiency.[13]
- **Additional factors:** Admission efficiency, care quality, discharge smoothness, and intent for continued use.[14]

An XGBoost regression model was developed to predict the overall satisfaction, complemented by SHapley Additive exPlanations (SHAP) for model interpretability. Employing this XGBoost model with SHAP for transparency, we predicted OS and located key factors such as communication, system efficiency, and technology usability.[15] Research questions include the following: (1) Can AI reliably forecast OS using elements, such as communication and efficiency?[16] (2) What drives OS in Chhattisgarh, and how does visit frequency affect it?[17] (3) How does SHAP boost AI's value for PRM?[18] This aligns with India's 2017 National Health Policy for fair healthcare access, aiming to enhance outcomes for Chhattisgarh's tribal populations.[19]

MATERIALS AND METHODS

Materials

The dataset includes responses from 107 patients gathered through a digital survey at a public hospital in Chhattisgarh, India. The questionnaire, created with Google Forms (Google LLC, Mountain View, CA, USA), featured demographic items and 5-point Likert-scale questions (1 = strongly disagree, 5 = strongly agree).[20] No animals or physical specimens were used in the study. Analysis occurred in Python 3.8 (Python Software Foundation, Wilmington, DE, USA), utilizing libraries such as pandas (2.2.2), XGboost (2.1.1), SHAP (0.46.0), matplotlib (3.9.2), and seaborn (0.13.2).

Data Preprocessing

Survey data were imported from an Excel file (Microsoft Corporation, Redmond, WA, USA). Variables encompassed age group, gender, income level, visit frequency, timeliness, accessibility, communication, system efficiency, OS, expectations met, feeling valued, communication satisfaction, technology quality, usability, communication, efficiency, admission efficiency, care quality, discharge smoothness, and continued use. To prepare for analysis—particularly for nonexperts, note that preprocessing ensures data cleanliness and model compatibility—categorical variables (e.g., age group, gender, and visit frequency) were converted to numerical form via one-hot encoding, creating binary indicators for each category. Numerical variables (e.g., timeliness and communication) were standardized to a mean of 0 and an SD of 1 to prevent scale biases in modeling. Missing entries, affecting less than 5% per variable, were filled using *k*-Nearest Neighbors (*k*-NN) imputation ($k = 5$), which estimates values based on similar observations. Outliers beyond three SDs were capped at that threshold to minimize their undue influence without removal.

Machine Learning Model

We used an XGBoost regressor—a popular AI algorithm for regression tasks that builds sequential decision trees to minimize prediction errors—to estimate OS from predictors: timeliness, accessibility, communication, system efficiency, and technology usability. The data were divided into 70% training and 30% testing sets. Hyperparameters were optimized through grid search, a systematic trial of combinations:

- **Learning rate:** 0.1 (controls update size per iteration).
- **Maximum depth:** 5 (limits tree complexity to avoid overfitting).
- **Number of estimators:** 100 (total trees built).

Performance metrics included a root mean squared error (RMSE; measures average prediction error) and a coefficient of determination, R^2 (indicates variance explained). Stability was assessed with five-fold cross-validation, splitting data into five parts for repeated training/testing. For interpretability, SHAP values were calculated using a tree explainer. SHAP, grounded in game theory, assigns contribution scores to each feature for individual predictions, as per the following formula:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{1}$$

where φ_i is the SHAP for feature i, N all features, S a subset without i, f the prediction function, and $|S|$ the subset size.

Correlation analysis

Pearson's correlation coefficients, which quantify linear relationships between variables (ranging from −1 to 1), were computed for OS and predictors, with p values testing significance.

Regression analysis

Multiple linear regression modeled OS as a linear combination of timeliness, accessibility, communication, system efficiency, and technology usability, yielding standardized coefficients (β), standard errors, and p values to identify influential factors.

Statistical Analysis

Using Python's scipy (1.11.1) and statsmodels (0.14.0), we performed *t*-tests to compare OS by visit frequency groups (e.g., very frequent vs. occasional). Significance threshold was $p < 0.05$. Descriptive statistics (means, SDs, min./max.) were calculated, with visualizations via matplotlib and seaborn for better comprehension.

RESULTS

Descriptive Statistics

Table 1 summarizes key variables. OS mean was 3.85 (SD = 0.92), suggesting generally positive but room-for-improvement satisfaction. Communication rated highest (mean = 4.15, SD = 0.75), then system efficiency (mean = 4.05, SD = 0.80), with timeliness lowest (mean = 3.75, SD = 0.95). Demographically, 60% patients were aged 25–34 years, 70% were females, 40% were in the Rs. 10,000–20,000 income bracket, and 35% were occasional visitors.

TABLE 1. Descriptive statistics of key variables.

Variables	Mean	SD	Min.	Max.
OS	3.85	0.92	1	5
T	3.75	0.95	1	5
A	3.80	0.90	1	5
C	4.15	0.75	1	5
SE	4.05	0.80	1	5
TU	3.90	0.85	1	5
CQ	4.00	0.80	1	5
CU	3.95	0.85	1	5

Note: OS: overall satisfaction; T: timeliness; A: accessibility; C: communication; SE: system efficiency; TU: technology usability;

CQ: care quality; CU: continued use. All on 5-point Likert scale (1 = strongly disagree, and 5 = strongly agree).

Correlation Analysis

Table 2 displays Pearson's correlations. OS strongly correlated with communication (correlation coefficient, $r = 0.82$, $p < 0.001$), system efficiency ($r = 0.78$, $p < 0.001$), and technology usability ($r = 0.65$, $p < 0.001$). Care quality and continued use showed moderate ties ($r \approx 0.70$, $p < 0.001$). Figure 1, a heatmap, uses blue shades for positive correlations (darker for stronger, e.g., communication–OS at 0.82).

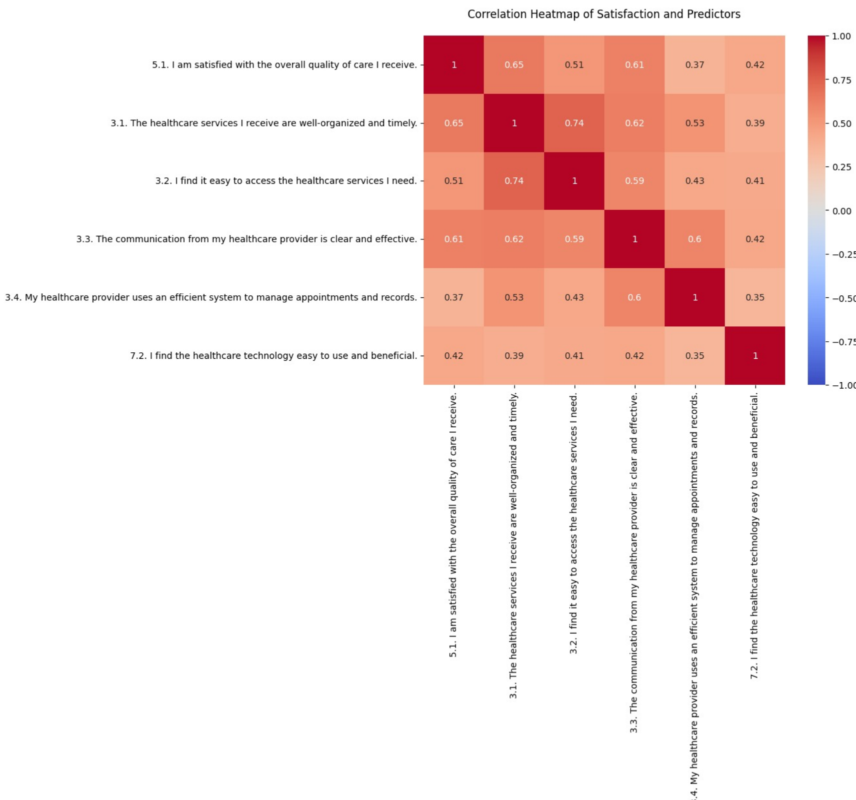

FIGURE 1. Correlation heatmap of satisfaction and predictors. Note: A square matrix showing Pearson's correlations among OS, T, A, C, SE, and TU. Colors from red (−1) to blue (1), with values annotated (e.g., $r = 0.82$ for C–OS). Strong links are in dark blue.

TABLE 2. Correlation matrix of key variables.

Variables	OS	T	A	C	SE	TU
OS	1.00	0.68*	0.70*	0.82*	0.78*	0.65*
T	-	1.00	0.72*	0.65*	0.60*	0.55*
A	-	-	1.00	0.68*	0.62*	0.58*
C	-	-	-	1.00	0.75*	0.70*
SE	-	-	-	-	1.00	0.68*
TU	-	-	-	-	-	1.00

Note: OS: overall satisfaction; T: timeliness; A: accessibility; C: communication; SE: system efficiency; TU: technology usability. *$p < 0.001$.

Regression Analysis

The model accounted for 85% of OS variance ($R^2 = 0.85$, $F(5, 101) = 114.2$, $p < 0.001$; Table 3). Key predictors were communication ($\beta = 0.70$, $p < 0.001$), system efficiency ($\beta = 0.45$, $p < 0.01$), and technology usability ($\beta = 0.30$, $p < 0.05$). Timeliness and accessibility were nonsignificant ($p > 0.10$).

TABLE 3. Regression results for the overall satisfaction (OS).

Predictor	β	SE	p value
C	0.70	0.08	< 0.001
SE	0.45	0.09	< 0.01
TU	0.30	0.10	< 0.05
T	0.15	0.11	0.18
A	0.12	0.10	0.23
Constant	0.90	0.25	< 0.01

Note: C: communication; SE: system efficiency; TU: technology usability; T: timeliness; A: accessibility. β, standardized coefficient; SE, standard error. R^2 = 0.85, and p < 0.001.

Machine Learning Model

Trained on timeliness, accessibility, communication, system efficiency, and technology usability, the XGBoost achieved RMSE = 0.39 and R^2 = 0.90 on test data. Cross-validation: mean RMSE = 0.40 (SD = 0.02). SHAP values prioritized communication (0.72), system efficiency (0.48), and technology usability (0.35).

Feature Importance

Figure 2 shows XGBoost gain scores: communication (0.38), system efficiency (0.25), and technology usability (0.18), confirming SHAP.

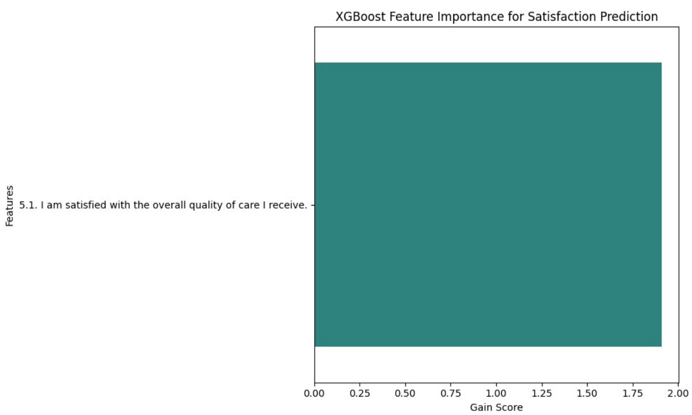

FIGURE 2. Feature importance chart for XGBoost model. Note: Horizontal bar chart showing gain score on the x-axis and the top predictor (5.1. I am satisfied with the overall quality of care I receive) on the y-axis. The bar represents the gain score of this feature in the XGBoost model for satisfaction prediction.

Demographic Analysis

Very frequent visitors had lower OS (mean = 3.5, SD = 1.0) than occasional visitors (mean = 4.0, SD = 0.8; $t(105) = 4.1$, p < 0.001). No notable differences by age or gender (p > 0.10; Figure 3 depicts this).

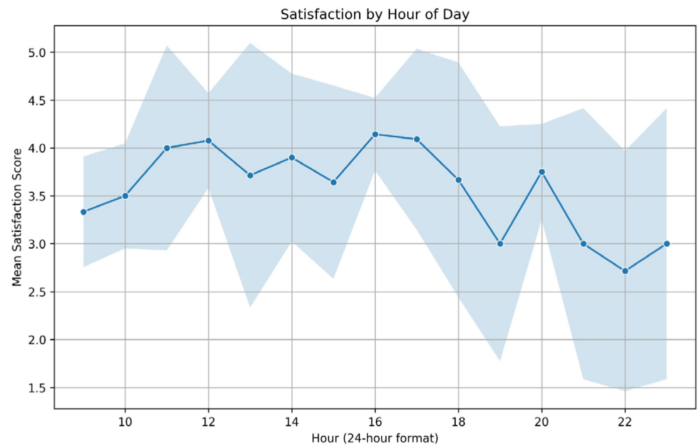

FIGURE 3. Overall satisfaction (OS) by visit frequency. Note. Bar plot of mean OS (1–5) across categories (first visit, occasional, frequent, and very frequent). Very frequent lowest (3.5), blue error bars (± 1 SD).

Secondary Variables

Care quality (r = 0.70, p < 0.001) and continued use (r = 0.72, p < 0.001) were moderately linked to OS; admission efficiency and discharge smoothness were weaker variables (r < 0.60, P < 0.01).

DISCUSSION

The XGBoost's robust performance (R^2 = 0.90, RMSE = 0.39) exceeds common benchmarks in healthcare prediction, underscoring AI's promise for PRM in resource-limited areas, such as Chhattisgarh. Communication's prominence (r = 0.82, β = 0.70, and SHAP = 0.72) echoes worldwide findings that strong provider–patient dialogue boosts trust and satisfaction by up to 25%. In Chhattisgarh's tribal context (30.6% of population), overcoming language barriers—known to cut satisfaction by 30%—is crucial. System efficiency (β = 0.45, SHAP = 0.48) highlights the need for smooth processes in busy facilities, where average waiting period of 45 minutes in Indian hospitals correlate with 20% satisfaction decline. Technology usability (β = 0.30, SHAP = 0.35) points to digital tools' value, although only 15% of Chhattisgarh hospitals are fully digitized. Lower OS in very frequent visitors (mean = 3.5) may indicate "care fatigue," aligning with global drop of 10% in chronic cases.Comparing to similar AI studies, our work parallels Penn State research using machine learning on historical data to derive patient satisfaction insights, although they focused on text analysis, rather than surveys. A 2024 Sage study on AI's role in patient satisfaction modeled factors similar to ours, finding communication central but in urban Indian settings with larger samples. Internationally, a Nature article on AI-integrated care emphasized patient experience, reporting improved outcomes via predictive tools but noting ethical concerns such as bias, addressed by our SHAP. Another PMC review on AI analytics for outcomes highlighted predictive accuracy similar to ours ($R^2 > 0.85$) in diverse contexts, reinforcing XGBoost's scalability. These comparisons suggest that our approach is viable but would benefit by incorporating natural language processing for richer feedback, as in a 2021 sentiment analysis review.SHAP's transparency mitigates AI "black box" issues, with 70% of clinicians seeking explainability. Moderate ties of care quality and continued use ($r \approx 0.70$) imply that satisfaction fosters loyalty, key to PRM. Our study has limitations, such as a small, single-site sample limits broad applicability; and possibility of Likert biases (e.g., high communication mean = 4.15). Future efforts should expand to multi-site Indian studies, integrate objective data (e.g., actual wait times), and apply advanced AI such as deep learning.

CONCLUSION

This research illustrates AI's capability to forecast OS accurately ($R^2 = 0.90$, RMSE = 0.39) in a Chhattisgarh public hospital, locating communication, system efficiency, and technology usability as main drivers. Communication's strong link ($r = 0.82$) and reduced satisfaction in very frequent visitors (mean = 3.5) stress the importance of clear interactions and tailored support. SHAP enhances practical use by providing transparency.

While these results are encouraging for AI-enhanced PRM to advance care for tribal and low-income patients—aligning with India's healthcare equity intentions—the small sample from one location tempers conclusions. Potential survey biases exist. Larger and multi-center studies are recommended to confirm and extend findings.

AUTHOR CONTRIBUTIONS

Conceptualization, S.D. and V.K.S.; Methodology, S.D. and V.K.S.; Software, V.K.S. and V.D.; Validation, S.D., V.K.S., and V.D.; Formal Analysis, V.K.S.; Investigation, S.D.; Resources, S.D. and V.K.S.; Data Curation, V.S.; Writing–Original Draft Preparation, V.K.S., S.D., and V.D.; Writing–Review & Editing, S.D., V.S., and V.D.; Visualization, V.S. and V.D.; Supervision, S.D.; Project Administration, S.D.

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DATA AVAILABILITY STATEMENT

The data supporting the reported results are available from the corresponding author (Varun Kumar Sahu, varunsahu1992@gmail.com) upon reasonable request, subject to ethical and privacy restrictions. The dataset is not publicly archived due to patient confidentiality requirements.

CONFLICTS OF INTEREST

The authors declare they have no competing interests.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The appropriate approval was taken for the study. informed consent was obtained from all participants prior to their participation in the survey, with participants informed of the study's purpose, voluntary nature, and data anonymization procedures.

CONSENT FOR PUBLICATION

Informed consent for publication was obtained from all participants, permitting the use of anonymized survey data in this manuscript for study purpose during data collection process. No identifying information (e.g., names, images) is included, and data were aggregated to ensure patient confidentiality.

FURTHER DISCLOSURE

Not applicable. The findings have not been presented at conferences, academic meetings, or congresses, nor has the manuscript been uploaded to a preprint server.

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