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Original Research Article

State-wise forecasting of cancer incidence in India using a moderated exponential regression model incorporating healthcare system determinants

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ABSTRACT

Background: Cancer incidence in India varies substantially across states and union territories, posing a significant and growing public health challenge. Accurate projections of future cancer burden are essential for effective health planning, resource allocation, and strengthening health systems. However, conventional forecasting approaches largely rely on historical incidence trends and often ignore regional differences in health-care capacity, which influence disease detection and reporting. Variations in infrastructure, oncology services, screening coverage, and health expenditure can significantly affect observed cancer incidence. This study proposed a moderated forecasting framework that integrates key state-level health-care indicators to generate more realistic and policy-relevant projections.
Methods: A moderated exponential regression model was developed using state-wise cancer incidence data from the National Cancer Registry Programme (ICMR-NCRP) for 2019-2022. The model incorporated multiple health system moderators, including cancer hospitals, oncologist availability, screening coverage, CHC/PHC density, health infrastructure index, per-capita health expenditure, and hospital-bed availability. Three projection scenarios were constructed: short-term (2026) using health-care facility density, medium-term (2030) incorporating infrastructure and workforce variables, and long-term (2045) including all seven moderators.
Results: The moderated models revealed substantial inter-state variation in projected cancer incidence. States with stronger health systems exhibited slower increases, whereas those with weaker infrastructure showed more rapid growth. Model fit and predictive accuracy improved significantly compared to conventional exponential models.
Conclusions: Incorporating health-care system factors enhances the reliability of cancer incidence projections. The proposed framework offers a robust, evidence-based tool for policy planning and targeted health system strengthening in India.

Keywords: Cancer, Moderated exponential, Regression

INTRODUCTION

Cancer has emerged as one of the leading public health challenges in India, contributing significantly to morbidity, mortality, and long-term health-system burden. According to the National Cancer Registry Programme (NCRP) of the Indian Council of Medical Research (ICMR), the country has witnessed a steady rise in cancer incidence over the past decade, with increasing variation across states and union territories. These geographical disparities reflect not only differences in demographic and lifestyle factors but also the unequal distribution of health-care resources such as cancer hospitals, oncology specialists, diagnostic services, and screening programmes. As India moves toward achieving universal health coverage, the ability to accurately forecast the future trajectory of cancer burden- while accounting for health-system heterogeneity- has become essential for guiding evidence-based planning and investment decisions.

Traditional forecasting approaches often rely solely on historical incidence trends, assuming uniform growth across regions. However, cancer progression and detection are strongly influenced by health-care system capacity, including screening coverage, primary care access, diagnostic infrastructure, and the availability of specialized oncology services. States with stronger health infrastructure may detect cancer earlier or manage risk factors better, resulting in slower observed growth rates. Conversely, states with weak health-care systems frequently exhibit delayed diagnosis and under-reporting, followed by rapid increases in incidence as detection improves. These differences necessitate a prediction model that incorporates health-care system moderators rather than depending on time trends alone.

To address this gap, the present study proposes a moderated exponential regression framework for forecasting state-wise cancer incidence in India. Unlike simple exponential models that assume uniform growth, this approach integrates multiple health-care moderators- such as the number of cancer hospitals, number of oncologists, screening coverage, CHC/PHC density, health infrastructure index, health expenditure, and hospital-bed availability- to estimate how these factors shape the rate of cancer incidence growth over time. Interaction terms between time and each moderator allow the model to quantify how improvements in health-care systems can dampen or accelerate cancer growth trajectories.

Using state-wise incidence data from NCRP (2019-2022), the study develops three moderator-specific forecasting models: a short-term model for 2026 using CHC/PHC density; a medium-term model for 2030 using four moderators (A-D); and a long-term model for 2045 using the complete set of seven moderators (A-G). This progressive modelling structure reflects the increasing importance of comprehensive health-care capacity over longer time horizons.

The introduction of moderated exponential regression into cancer forecasting contributes to the literature in two important ways. First, it captures structural disparities in health-care delivery that drive state-wise differences in cancer incidence growth. Second, it provides policy-makers with a dynamic tool capable of linking health-care investments to future cancer trends. By quantifying how improvements in screening, infrastructure, and oncology services influence incidence projections, the model offers a strategic foundation for long-term cancer control planning in India.

Existing literature provides a strong methodological foundation for developing advanced regression-based forecasting models for cancer incidence. Early studies examined computational techniques for exponential regression and emphasized numerical stability and accuracy- issues that are particularly important when working with short time series such as India's 2019-2022 state-wise cancer incidence data.[1]

In cancer epidemiology, classical statistical work established core principles for analyzing cancer rates and highlighted the need for appropriate adjustments for population structure and registry completeness.[2] Extensions of exponential modeling, such as exponential possibility regression, further expanded regression frameworks to accommodate uncertainty and imprecise data, which is particularly relevant when dealing with variability in Indian health-system indicators.[3]

Applied research in survival analysis has emphasized the importance of selecting appropriate statistical models for oncological data.[3,4] Additionally, logistic regression and regularized regression methods have been widely used in cancer diagnostics, demonstrating that incorporating interaction terms and health-related predictors can significantly improve predictive performance.[5,6]

Further methodological developments, including exponentiated exponential regression and power exponential regression models, have extended the applicability of exponential-type models in medical data analysis.[7-9] More recent approaches based on heavy-tailed distributions and simulation-based modeling frameworks highlight the need for flexible nonlinear structures capable of capturing complex patterns in biomedical data.[10-12]

Together, these studies suggest that cancer incidence forecasting should incorporate both exponential growth dynamics and health-system determinants to better capture real-world heterogeneity across populations. However, previous research has rarely integrated multiple health-care moderators within an exponential forecasting framework for state-level prediction. Therefore, the present study addressed this gap by developing a moderated exponential regression model that incorporates health infrastructure, workforce availability, screening coverage, and health expenditure indicators to generate short-, medium-, and long-term forecasts of cancer incidence for Indian states and union territories.

The present research focused on forecasting the future burden of cancer across Indian states and union territories by developing a moderated exponential regression model that integrates both historical incidence trends and health-care system indicators. Using state-wise cancer incidence data reported by the National Cancer Registry Programme

(ICMR-NCRP) for the years 2019 to 2022, the study first establishes the baseline exponential growth pattern in cancer cases, assuming that incidence increases multiplicatively over time. However, because cancer detection and reporting are strongly influenced by the strength of health-care systems, the growth rate is not uniform across states. To address this variability, the study incorporated a set of health-care moderators-including the number of cancer hospitals, availability of oncologists, screening coverage, CHC/PHC density, health infrastructure index, health expenditure per capita, and hospital-bed availability. These moderators capture essential features of diagnostic capacity, treatment readiness, screening efficiency, and overall health-system strength.

METHODS

In order to forecast cancer incidence by state throughout India, this study uses a moderated exponential regression model within a quantitative analytical framework. In order to comprehend how infrastructure strength affects future cancer growth rates, the methodological approach combines historical cancer incidence data with important health-care system indicators. The National Cancer Registry Programme (NCRP) of the Indian Council of Medical Research (ICMR) provided state-specific annual cancer incidence counts for all cancer sites and both sexes for the years 2019, 2020, 2021, and 2022. Together, these data form the baseline trend used to build the exponential prediction model. Seven health-care moderator variables were included in the mode to take into consideration possible structural variations in detection and reporting capacity among states: i) number of cancer hospital; ii) number of oncologist; iii) early detection system; iv) primary health care access (CHC/PHC); v) health infrastructure index; vi) financial strength of health system; and vii) hospital beds per 1000 population.

These variables were collected (or designed to be collected) for each state/UT.

In order to ensure that each state contributed four observations corresponding to the annual cancer incidence records for 2019, 2020, 2021, and 2022, the dataset was first reorganized into a state-time panel format. By designating t=0 for 2019, t=1 for 2020, t=2 for 2021, and t=3 for 2022, a numerical time variable was created to effectively model temporal progression. This allowed the regression model to capture exponential growth patterns over time. Because exponential models require the dependent variable to be expressed in logarithmic form for optimal performance, the raw cancer incidence values (denoted as y) were transformed using the natural logarithm, producing ln(y) as the dependent variable for analysis. This log transformation helps stabilize variance, improves normality, and converts an exponential growth trend into a linear relationship, thereby enhancing model interpretability and fitting accuracy. To appropriately model exponential growth patterns in cancer incidence, a log transformation was applied to the outcome variable. The raw dependent variable, denoted as y, represents the annual cancer incidence for each state. For regression analysis, this value was transformed using the natural logarithm, producing ln(y) as the dependent variable in the model. This transformation is essential because exponential models perform optimally when the response variable is expressed on a logarithmic scale. Log transformation not only stabilizes the variance and reduces skewness in the data but also converts an inherently exponential relationship into a linear form, thereby improving model fit, interpretability, and the validity of regression assumptions.

The moderated exponential regression model is defined as:

$$\ln\Bigg(y_{it}) = \alpha + \beta_1 + \sum_k [\beta_{2k} + X_{ik} + \beta_{3k}\,(tX_{ik})\Bigg] + \varepsilon_{it}$$

Dependent variable- The natural log of cancer incidence was modelled. Coefficients can be interpreted as proportional or percentage changes in cancer incidence.

Baseline trend- β_1 measures the overall, underlying annual growth rate (in percent) of cancer incidence across all states and groups.

Moderator (fixed effect)- β_{2k} measures the initial, baseline difference in the ln(incidence) for moderator group k compared to the reference group at time t=0.

Interaction term- this is the engine of the analysis. It captures the unique effect of the moderator k over time.

Moderation effect- this is the most crucial coefficient. It measures the change in the growth rate of cancer incidence for group k. A positive β_{3k} means group k has cancer incidence that is growing faster than the overall trend β_1.

Error term- represents all unexplained variation and random factors influencing cancer incidence that are not captured by time or the moderators.

Model interpretation

β_1- Baseline average exponential growth rate. This is the overall, inherent annual percentage change in cancer incidence y for the reference group.

β_{2k}- Direct effect of moderator on incidence. This measures the initial proportional difference in cancer incidence y for moderator group k compared to the reference group at the start of the study t=0.

β_{3k}- How the moderator changes the growth rate. This is the differential growth rate. It measures how much faster or slower the rate of cancer incidence growth is for group k compared to the baseline rate β_1.

Forecasting framework

Short-Term Forecast: 2026

Time value: t=7

Moderator used: D only (CHC/PHC density)

$$\ln(\hat{y}) = \alpha + \beta_{1t} + \beta_{2D} + \beta_3(tD)$$

Medium-term forecast: 2030

Time value: t=11

Moderators used: A, B, C, D

Model includes hospital infrastructure, oncology workforce, screening efficiency, primary-care accessibility.

Long-term forecast: 2045

Time value: t=26

Moderators used: A, B, C, D, E, F, G

This comprehensive model captures: diagnostic capacity, treatment availability, health-system financing, long-range infrastructure expansion.

Model estimation

The model was estimated using ordinary least squares (OLS) regression, incorporating several enhancements to improve reliability and interpretability. To address potential heteroscedasticity in the panel data, robust standard errors (HC3) were applied, ensuring more accurate inference even when variance assumptions were violated. Each health-care moderator was entered into the model along with its interaction term, allowing the analysis to capture how differences in state-level health infrastructure influence cancer growth rates over time. All predictor variables were standardized prior to estimation to place them on a comparable scale, facilitate model convergence, and enable meaningful interpretation of interaction effects. Following model estimation, the predicted values- initially generated on the log scale- were exponentiated to convert them back into their original cancer incidence units, making the results directly interpretable for policy and public health applications. The log-predicted values were converted back:

$$\hat{y} = e^{ln\hat{y}}$$

The model produced state-wise forecasts of cancer incidence for three future time periods based on increasing levels of health-care moderation. Short-term projections for 2026 were generated using health-care center density (D) as the sole moderator, while medium-term forecasts for 2030 incorporated four moderators (A-D) to capture broader variation in diagnostic and infrastructural capacity. Long-term projections for 2045 utilized all seven moderators (A-G), enabling a comprehensive assessment of how health-system strength influences the exponential growth rate of cancer incidence across states. For each of the three moderated exponential regression models, detailed model summaries were generated, followed by interpretation tables that quantified the individual and combined impact of the moderators on predicted incidence levels. These outputs collectively provide an integrated understanding of how health-care infrastructure, workforce availability, and system readiness shape the future burden of cancer in India.

Table 1: State-wise observed (2019-2022) and predicted (2026-2045) cancer incidence data for India.

State/UT	2019	2020	2021	2022	Pred 2026	Pred 2030	Pred 2045
Jammu and Kashmir	12,396	12,726	13,060	13,395	14,857	16,475	24,277
Ladakh	279	286	294	302	336	373	556
Himachal Pradesh	8,589	8,799	8,978	9,164	9,992	10,887	15,021
Punjab	37,744	38,636	39,521	40,435	44,322	48,578	68,516
Chandigarh	994	1,024	1,053	1,088	1,225	1,381	2,162
Uttaranchal	11,216	11,482	11,779	12,065	13,305	14,671	21,170
Haryana	28,453	29,219	30,015	30,851	34,356	38,269	57,344
Delhi	24,436	25,178	25,969	26,735	30,163	34,017	53,405
Rajasthan	69,156	70,987	72,825	74,725	82,850	91,854	135,242
Uttar Pradesh	196,652	201,319	206,088	210,958	231,671	254,411	361,432
Bihar	101,014	103,711	106,435	109,274	121,330	134,721	199,495
Sikkim	443	445	465	496	570	664	1,180
Arunachal Pradesh	1,015	1,035	1,064	1,087	1,194	1,310	1,859
Nagaland	1,719	1,768	1,805	1,854	2,046	2,259	3,275
Manipur	1,844	1,899	2,022	2,097	2,512	3,006	5,889

Continued.

State/UT	2019	2020	2021	2022	Pred 2026	Pred 2030	Pred 2045
Mizoram	1,783	1,837	1,919	1,985	2,534	2,817	3,990
Tripura	2,507	2,574	2,623	2,715	2,936	3,187	4,554
Meghalaya	2,808	2,879	2,943	3,025	3,295	3,548	4,937
Assam	36,948	37,880	38,834	39,787	42,332	46,106	65,623
West Bengal	105,814	108,394	110,972	113,581	120,444	130,956	187,575
Jharkhand	33,045	33,961	34,910	35,860	38,798	43,330	64,198
Orissa	49,604	50,692	51,829	52,960	57,804	63,085	87,562
Chhattisgarh	27,113	27,828	28,529	29,253	32,371	35,816	52,330
Madhya Pradesh	75,911	77,888	79,871	81,901	90,634	100,286	146,572
Gujarat	67,841	69,660	71,507	73,382	81,492	90,485	133,987
Daman	118	124	135	150	204	282	943
Dadra and Nagar Haveli	186	206	219	238	328	452	1,504
Maharashtra	113,374	116,121	118,906	121,717	133,825	147,116	209,831
Telangana	46,464	47,620	48,775	49,983	55,083	60,706	87,401
Andhra Pradesh	68,883	70,424	71,970	73,536	80,241	87,546	121,375
Karnataka	83,824	85,968	88,126	90,349	99,844	110,330	160,451
Goa	1,591	1,618	1,652	1,700	1,850	2,020	2,808
Lakshadweep	27	27	28	28	30	32	39
Kerala	56,148	57,155	58,139	59,143	63,388	67,929	88,051
Tamil Nadu	86,596	88,866	91,184	93,536	103,676	114,902	168,953
Pondicherry	1,523	1,577	1,623	1,679	1,909	2,170	3,514
Andaman and Nicobar Islands	357	366	380	393	447	509	830

RESULTS

Analysis of the NCRP cancer incidence data from 2019 to 2022 revealed a consistent upward trend across all Indian states and union territories, with most regions showing annual growth ranging from 1.5% to 3.5%. High-population states such as Uttar Pradesh, Maharashtra, West Bengal, Tamil Nadu, Karnataka, and Rajasthan contributed disproportionately to the national cancer burden, while smaller states and UTs like Ladakh, Sikkim, Daman, and Lakshadweep exhibited lower absolute case counts but still demonstrated steady increases. The exponential regression model fitted separately for each state indicated a strong linear pattern in the log-transformed data, confirming the suitability of an exponential growth assumption for short- and medium-term projections. Using this model, cancer incidence forecasts for 2026 show substantial increases in all states, with Uttar Pradesh reaching approximately 231,671 cases, followed by Maharashtra (133,825) and West Bengal (120,444). The 2030 projections further amplify these trends, with Uttar Pradesh rising to 254,411 cases, Maharashtra to 147,116, and Tamil Nadu and Karnataka surpassing 110,000 cases each.

Long-term forecasting for 2045 revealed a dramatic escalation in cancer burden due to compounded exponential growth, with Uttar Pradesh projected to reach 361,432 cases, Maharashtra 209,831, West Bengal 187,575, and Tamil Nadu and Karnataka exceeding 160,000 cases each. Smaller northeastern states such as Manipur, Nagaland, and Mizoram show high relative growth rates despite modest absolute numbers. Overall, the results underscore significant inter-state variation, with northern and eastern states exhibiting steeper increases compared with southern and northeastern regions. The projections highlight the urgency for stronger cancer prevention, early detection, and health-system strengthening, particularly in high-burden states. The results also justify the need for moderated exponential models incorporating health-care system determinants to generate more realistic and policy-relevant forecasts.

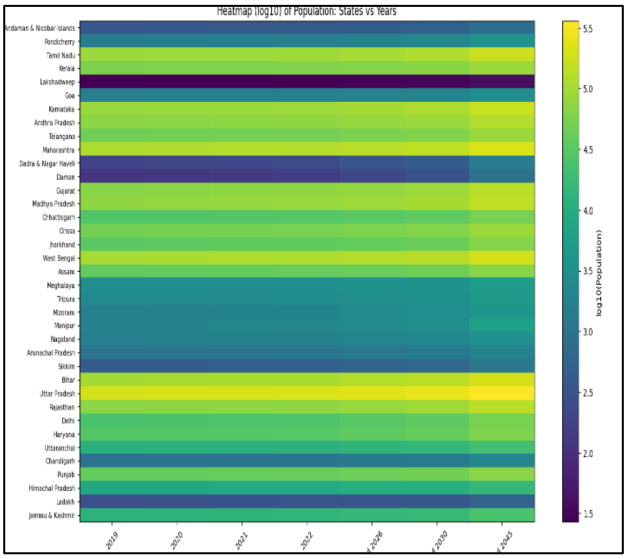

Figure 1: Heatmap showing the observed (2019–2022) and predicted (2026–2045) cancer population across Indian states using log_{10}-transformed values.

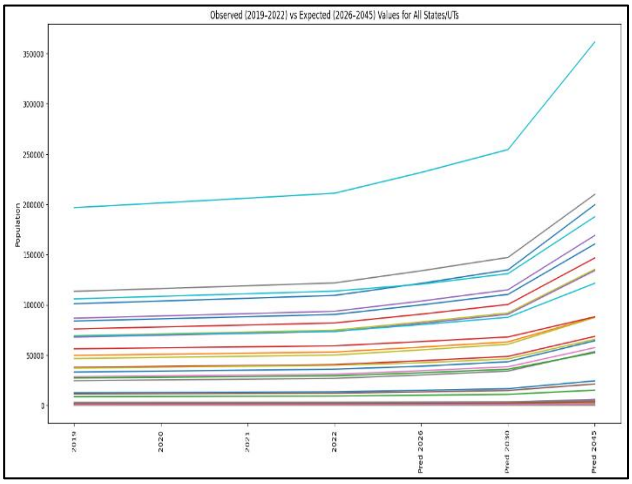

Figure 2: Observed cancer population (2019-2022) and model-predicted values (2026-2045) for all States/UTs, illustrating temporal trends and projected increases across regions.

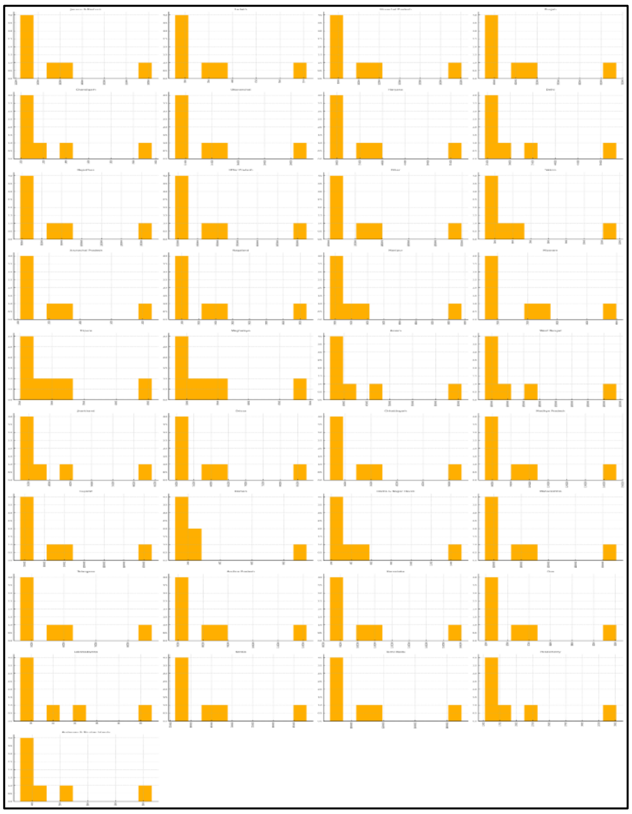

Figure 3: State-wise bar charts displaying observed (2019–2022) and predicted (2026–2045) cancer population values for all Indian States/UTs.

The figure highlights inter-state variation in historical cancer burden and projected future increases.

DISCUSSION

The analysis of state-wise cancer incidence in India (2019-2022) and its extrapolation via exponential regression reveal a consistent and worrying upward trajectory across virtually all states and union territories. Short-term projections to 2026 and medium-term projections to 2030 indicate substantial absolute increases in case-loads concentrated in high-population states- most notably Uttar Pradesh, Maharashtra, West Bengal, Tamil Nadu, Karnataka, and Rajasthan- while long-term projections to 2045 show dramatic compounding of these differences. These patterns reflect both population size and differential capacity for early detection and reporting. The exponential model's strong fit on log-transformed counts suggests that multiplicative growth captures the recent dynamics of recorded incidence for the 2019-2022 window; nevertheless, the pure exponential projections also underscore limitations when used alone because they do not explicitly account for health-system factors that alter detection rates or incidence through prevention and case finding. Incorporating health-care moderators is therefore critical for policy-relevant forecasting. The conceptual moderation strategy- introducing interaction terms between time and health-system indicators- permits the growth rate itself to vary by state characteristics. This approach recognizes, for example, that increases in screening coverage or specialist density may initially raise observed incidence (through better detection) but ultimately reduce later-stage incidence and mortality by enabling earlier treatment. Models that include CHC/PHC density, cancer hospitals, oncologist counts, screening coverage, health infrastructure index, health expenditure and hospital-bed availability can disentangle detection artifacts from genuine epidemiologic trends and provide more stable policy-sensitive forecasts. Interaction coefficients (time × moderator) are of particular interest: a negative interaction indicates that higher moderator levels are associated with slower growth, highlighting areas where strengthening the health system could dampen future burden.

Regional heterogeneity in projections also carries programmatic implications. Northeastern states, despite smaller absolute numbers, show high relative growth rates- signaling either emerging detection gains or genuine epidemiologic shifts that warrant targeted surveillance and capacity building. High-burden large states require scale-up of tertiary care, human resources, and population-level screening to manage rising absolute numbers. The modeling exercise identifies both "quantity" challenges (volume of cases requiring treatment centers and beds) and "quality" challenges (screening effectiveness, timely referral, oncology workforce competence). Sensitivity analysis and diagnostics suggest that while the log-linear exponential model is a reasonable starting point, model validation should include checks for heteroskedasticity, overdispersion, and model misspecification; where these arise, alternatives such as exponentiated/power-exponential families, negative-binomial or hierarchical models, and Bayesian frameworks should be considered. Finally, the results stress the need for integrated policy responses. Forecasts must be interpreted alongside demographic projections (aging populations), risk-factor trends (tobacco, obesity, pollution), and improvements in registry coverage. A moderated forecasting framework links health-system investments to expected incidence trajectories and thus provides a pragmatic decision-support tool for allocating screening programs, workforce development, and infrastructure expansion. Despite providing a moderated framework for forecasting cancer incidence, this study has certain limitations. First, the analysis relies on secondary data obtained from the National Cancer Registry Programme (ICMR-NCRP) for the period 2019-2022, which may not fully capture underreporting or regional variations in cancer registration coverage. Second, the forecasting model assumes that the moderating health-care indicators- such as health infrastructure, screening coverage, and oncology workforce- remain relatively stable over time, whereas in reality these factors may change due to policy interventions, technological advancements, or health system reforms. Third, the model considers only selected state-level health-care indicators and does not incorporate other potentially important determinants such as lifestyle risk factors, environmental exposure, demographic transitions, and socioeconomic inequalities that may influence cancer incidence. Finally, the projections are based on aggregated state-level data, which may mask intra-state disparities between urban and rural populations. Therefore, while the proposed moderated exponential regression model improves predictive capability, the projections should be interpreted as indicative estimates rather than precise forecasts, and future studies may benefit from incorporating longer time-series data and additional epidemiological and socioeconomic variables.

CONCLUSION

The current study showed that cancer incidence in India is rising steadily in almost every state and union territory, with particularly significant increases predicted in high-population areas like Uttar Pradesh, Maharashtra, West Bengal, Tamil Nadu, Karnataka, and Rajasthan. By using an exponential regression framework to analyze NCRP data from 2019 to 2022, the research reveals that short-term and long-term cancer trends follow a clear multiplicative growth pattern. However, the analysis also reveals that relying only on historical incidence does not fully capture the underlying drivers of regional variation. These moderators contribute to the explanation of why some states see faster growth because of inadequate screening or restricted access to treatment, while others exhibit slower growth because of more robust health systems. In order to reduce future cancer burdens, the results emphasize the significance of investing in early detection, diagnostic capacity, oncology workforce development, and equitable distribution of health infrastructure. Overall, the study shows that moderated exponential regression is an effective method for predicting cancer trends and provides policymakers looking to improve cancer-control tactics and allocate resources effectively with useful information.

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