Data-Driven Insights into Fertility Trends: An Explainable AI Approach to Forecasting and Policy Implications

Anya Deshpande

Received September 23, 2025
Accepted October 27, 2025
Electronic access November 15, 2025

Declining fertility rates in the United States present complex challenges for healthcare planning, economic stability, and reproductive justice. While prior demographic research has documented these shifts, relatively few studies have employed interpretable machine learning methods that combine forecasting accuracy with transparency. This study examines fertility dynamics in California and Texas from 1973 to 2020, applying artificial intelligence (AI) models to project future birth totals and evaluate reproductive health indicators. Using data obtained from the Open Science Framework, the Prophet time-series model was applied to forecast annual births through 2030 and benchmarked against a linear regression baseline. Prophet consistently outperformed regression, yielding substantially lower error in both states (California: RMSE = 6,231.41, MAPE = 0.83%; Texas: RMSE = 8,625.96, MAPE = 1.84%). To enhance interpretability, XGBoost regression combined with SHapley Additive exPlanations (SHAP) quantified the relative influence of predictors. Miscarriage totals, abortion access, and state-level variation emerged as the most influential drivers of fertility outcomes. Forecasts for both states suggest continued long-term declines in births, punctuated by short-term oscillations in the late 2020s, which may reflect the influence of policy or economic volatility. These results underscore the importance of combining forecasting accuracy with interpretability. By integrating Prophet with SHAP, this study provides transparent, data-driven insights into the demographic and policy factors shaping reproductive outcomes. The findings demonstrate the potential of explainable AI to inform healthcare planning, guide reproductive health policy, and support equitable responses to demographic change.

Keywords: fertility forecasting, reproductive health, time-series modeling, SHAP (SHapley Additive exPlanations), Prophet, XGBoost, Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Linear regression

Introduction

Fertility rates[1] in the United States have been steadily declining for several decades, raising urgent questions about demographic sustainability, economic growth, and reproductive justice. Lower fertility rates[1] influence multiple dimensions of society, including workforce participation, healthcare system planning, and population structure. As policymakers and healthcare providers grapple with these long-term shifts, there is growing recognition of the need for more precise forecasting tools[2] that can illuminate both the direction of fertility trends and the factors driving them.

Prior research has identified several contributors to fertility decline, including contraceptive use, abortion access, socioeconomic conditions, and cultural shifts such as delayed childbearing. However, most of this work has relied on descriptive statistics or traditional forecasting models[2] that often lack the transparency needed to interpret underlying drivers. Furthermore, many studies have not fully connected observed fertility patterns to the broader policy landscape, including watershed legal decisions like Roe v. Wade (1973)[3] and Planned Parenthood v. Casey (1992)[4] , or more recent changes in reproductive healthcare access.

Artificial intelligence (AI) and machine learning provide new opportunities to address these gaps. Unlike traditional methods, interpretable AI models not only enhance predictive precision but also reveal the relative influence of social, medical, and policy factors on fertility outcomes. SHapley Additive exPlanations (SHAP)[5] , for example, allow researchers and policymakers to examine which predictors exert the strongest influence on model outputs, offering insights that are both statistically grounded and actionable.

This study applies time-series forecasting[2] and interpretable AI to fertility data from California and Texas spanning nearly five decades (1973–2020). These two states provide instructive contrasts: California with its comparatively broad reproductive healthcare access, and Texas with more restrictive policies and demographic volatility. The study has three main objectives:

1. Forecast annual birth totals in California and Texas from 2021–2030 using the Prophet[6] model.

2. Identify and interpret the most influential reproductive

health predictors using SHAP[5] applied to XGBoost[7] regression.

3. Evaluate model accuracy against a linear regression baseline using RMSE[8] and MAPE[9] .

By integrating forecasting accuracy[2] with interpretability, this research advances the study of fertility decline beyond descriptive analysis. It contributes to demographic and public health scholarship by providing transparent, data-driven insights into how healthcare access, policy environments, and demographic change collectively shape reproductive outcomes.

Methodology

This study employed an observational, cross-sectional, and retrospective research design. Rather than intervening or manipulating variables, the study analyzed historical fertility-related data to uncover patterns and generate forecasts. This design was chosen to capture long-term demographic trends and evaluate predictive modeling performance without the constraints of experimental research.

No human participants were directly involved. The sample consisted of state-level reproductive health statistics for California and Texas spanning 1973–2020. Data included annual totals of births, abortions, pregnancies, and miscarriages. Because the dataset was aggregated, anonymized, and publicly available, there were no individual-level demographic identifiers such as age, race, or income.

Data were obtained from the Open Science Framework (OSF)[10] U.S. fertility measures dataset (1973–2020). This repository compiles official state-level statistics from government sources such as the CDC[11] , NCHS (National Center for Health Statistics)[12] , and state public health departments[13] , ensuring historical consistency and reproducibility. The dataset is freely available for download in CSV format from the OSF[10] platform. No new surveys, experiments, or recruitment were conducted; the study relied entirely on archival data.

Variables and Measurements:

- Forecast Variable: Annual total births (1973–2020).
- Predictor Variables: Abortion totals, miscarriage totals, pregnancy rates, abortion rates, and state identifiers.
- Measurement Tools: Prophet[6] (time-series forecasting[2]), XGBoost[7] (machine learning regression), and SHAP[5] (interpretability and feature importance).
- Evaluation Metrics: Root Mean Squared Error (RMSE)[8] and Mean Absolute Percentage Error (MAPE)[9] were used to assess predictive accuracy.

Software and Environment:

Analyses were performed in Python (version 3.9). All scripts were run in Jupyter Notebook. Required open-source libraries included:

- pandas (for data cleaning and manipulation)
- numpy (for mathematical operations)
- prophet[6] (time-series forecasting[2] , installed via pip install prophet)
- scikit-learn (for model validation and baseline regression)
- xgboost[7] (machine learning regression, installed via pip install xgboost)
- shap[5] (interpretability, installed via pip install shap)
- matplotlib and seaborn (for data visualization).

Procedure:

1. Data Download and Preparation
   (a) Download fertility data CSV files from OSF[10] .
   (b) Import data into Python using pandas.
   (c) Filter the dataset to include only California and Texas (1973–2020).
   (d) Ensure consistency of column names and convert all date fields into datetime format.
   (e) Handle missing values by forward-filling (ffill) or interpolation where appropriate.
   (f) Create separate time-series objects for births, abortions, miscarriages, and pregnancies.
2. Forecasting with Prophet[6]
   (a) Prophet requires two columns: ds (date) and y (value). Data were reformatted accordingly.
   (b) Separate Prophet models were trained for each variable (births, abortions, miscarriages, pregnancies).
   (c) Forecast horizons were set to extend through 2030.
   (d) Prophet decomposed the series into trend and seasonal components, producing forward projections with confidence intervals.
3. Regression Modeling with XGBoost[7]
   (a) Predictor dataset was structured with births as the dependent variable (y) and abortion totals, miscarriage totals, pregnancy rates, and abortion rates as independent variables (X).

(b) Train-test splits (80/20) were used for evaluation.

(c) Hyperparameters were tuned via grid search (max_depth, eta, n_estimators).

(d) XGBoost regression was applied to model non-linear relationships.

4. Interpretability with SHAP[5]

(a) SHAP values were calculated for each predictor.

(b) Feature importance plots and dependence plots were generated to interpret how predictors influenced birth totals.

(c) Results quantified which reproductive health indicators most strongly contributed to the model's predictions.

5. Validation Against Baseline Models

(a) A linear regression model was trained as a baseline.

(b) RMSE[8] and MAPE[9] were calculated for Prophet[6], XGBoost[7], and baseline models.

(c) Model performance comparisons ensured that improvements were attributable to advanced methods rather than chance.

Analysis combined time-series forecasting[2] and explainable AI. Prophet[6] decomposed time-series into trend and seasonal components, enabling forward projections. XGBoost[7] modeled non-linear relationships among predictors, while SHAP[5] quantified each feature's contribution to predictions. Visualization of forecasts and SHAP[5] values ensured interpretability.

Because the dataset was public, anonymized, and aggregated at the state level, no institutional review board (IRB) approval was required. No private medical records or identifiable personal data were used. The study adhered to principles of responsible AI research, emphasizing transparency, fairness, and interpretability. Potential biases due to state-level policy differences and dataset limitations were addressed through model validation and explainability techniques.

Results

Figure 1 illustrates California's abortion[14] rate over time, which rose sharply after Roe v. Wade (1973)[3], peaked in the late 1980s, and declined steadily from the 1990s onward. This trend reflects the expansion and subsequent regulation of abortion access, as well as the growing influence of contraception and reproductive health policies.

From a modeling perspective, these historical patterns are essential to both Prophet[6] and XGBoost[7]. Prophet captures the long-term decline and short-term fluctuations, using past variability to forecast future abortion[14] totals. Meanwhile, XGBoost

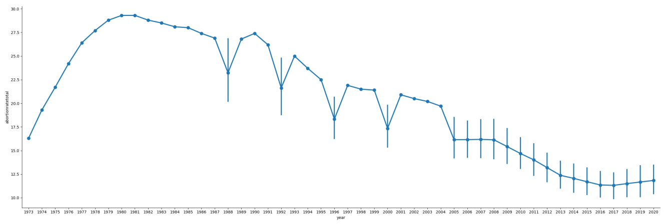

Fig. 1 *Abortion rate in California, 1973–2020. The abortion rate rose steadily after Roe v. Wade (1973)[3], peaking in the late 1980s before entering a long-term decline. This trend reflects changing access to reproductive healthcare, policy restrictions in the 1990s, and the wider adoption of effective contraception. Error bars capture reporting variability across time.*

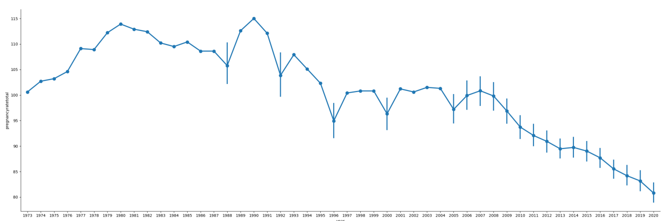

Fig. 2 *Pregnancy rate in California, 1973–2020. Pregnancy rates increased through the late 1970s, stabilized in the 1980s, and then began a steady decline from the mid-1990s onward. These shifts reflect improvements in contraception, public health campaigns, socioeconomic changes, and delayed childbearing.*

incorporates abortion totals and rates as predictor variables, with SHAP[5] analysis confirming their strong influence on birth outcomes. This connection demonstrates how shifts in abortion access—visible in Figure 1—directly inform the model's ability to predict fertility dynamics. Figure 2 shows pregnancy rates increasing through the late 1970s, stabilizing in the 1980s, and declining consistently from the mid-1990s onward. These changes align with improved access to contraception, delayed childbearing, and evolving cultural and socioeconomic pressures.

Prophet[6] models these declines by decomposing the time series into trend and seasonal components, producing forward projections that reflect the continuation of these downward trajectories. In XGBoost[7], pregnancy rates serve as a key predictor variable; SHAP[5] values demonstrate their consistent contribution to explaining birth totals. Thus, the trend captured in Figure 2 not only reveals historical shifts but also strengthens model interpretability by showing how reductions in pregnancies correlate with future declines in births.

Synthesis of graphs

Together, Figures 1 and 2 demonstrate a parallel decline in abortion[14] and pregnancy rates after the 1990s, reflecting broader improvements in contraception, family planning, and reproductive autonomy. The simultaneous reduction in unintended pregnancies and abortion demand highlights how structural changes in healthcare and policy shape multiple aspects of reproductive behavior.

For Prophet[6] , the alignment of declining abortion[14] and pregnancy rates reinforces the model's forecasts of sustained long-term declines in births, with only minor rebounds. For XGBoost[7] , the synthesis underscores why abortion and pregnancy variables are among the most influential predictors: SHAP analysis[5] shows that both features strongly shape model outputs, and their joint decline helps explain the projected decreases in future fertility. By linking these two indicators, the models capture not only individual variable effects but also their combined impact on long-term demographic change.

Utilizing SHAP Library

This is a SHAP (SHapley Additive exPlanations)[5] in figure 3 summary plot visualizing feature importance in a machine learning model. The x-axis represents the mean absolute SHAP value, indicating the average contribution of each feature to the model's predictions. The y-axis lists the features in descending order of their importance.

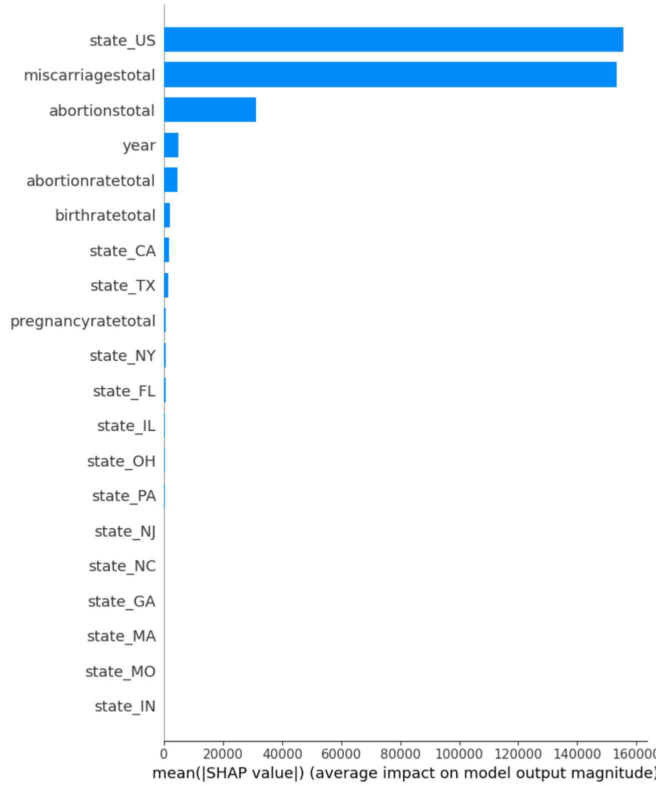

Fig. 3 *SHAP summary plot of feature importance. The machine learning model identified miscarriage totals, abortion access, and state-level differences as the most influential predictors of fertility outcomes. SHAP values quantify how strongly each variable contributes to the predictions.*

The most impactful features on the model's output are

1. state_US
2. miscarriagetotal
3. abortionstotal

The SHAP[5] plot highlights the significant influence of factors like state_US, miscarriagetotal, and abortionstotal on a machine learning model's predictions. These variables can be tied to broader public health concerns, access to healthcare, and policy differences across states. For instance, the importance of abortionstotal and abortionratetotal may reflect the ongoing impact of restrictive abortion[14] laws and disparities in access to reproductive healthcare. Following the overturning of Roe v. Wade[3] , many states implemented strict abortion laws, creating significant disparities in access to abortion services. This ties directly to current debates surrounding reproductive rights, federal vs. state policies, and the challenges many individuals face in obtaining care.

Similarly, miscarriagetotal[15] being a key factor in the model could indicate disparities in access to maternal healthcare, highlighting broader systemic issues such as rising maternal mortality[16] rates and inconsistent quality of care. Current events, such as the ongoing efforts to expand Medicaid coverage for maternal care and postpartum support, align with this insight. Meanwhile, the prominence of state_US underscores how state-specific policies, healthcare systems, and cultural differences impact health outcomes. This ties into larger discussions about the need for consistent, equitable healthcare access across all states, regardless of state-level policies.

To mitigate these issues, several strategies can be implemented. First, expanding access to reproductive healthcare is crucial. This can include increasing funding for clinics that offer affordable and comprehensive services, such as prenatal care, miscarriage management, and abortion services, especially in underserved areas. Supporting telemedicine for reproductive health can also help bridge access gaps in states with restrictive laws. Additionally, advocating for federal policies to ensure equitable access to healthcare across all states is vital, as state-level disparities often leave many without essential care.

Education and awareness campaigns also play a key role in addressing these issues. Public education initiatives can help reduce stigma around reproductive health while providing accurate, culturally relevant information to diverse communities. Investments in maternal and child health programs are another important step. Programs that offer prenatal care, miscarriage[15]

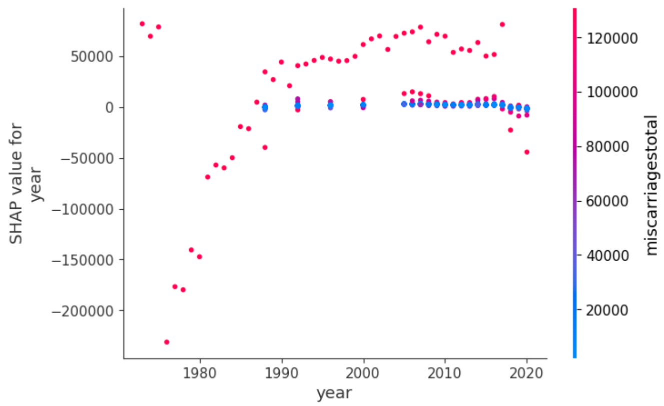

Fig. 4 SHAP values: miscarriages over time. *The influence of miscarriages on the model increased over time, reflecting both improvements in reporting and possible rises in high-risk pregnancies associated with delayed childbearing and chronic health conditions.*

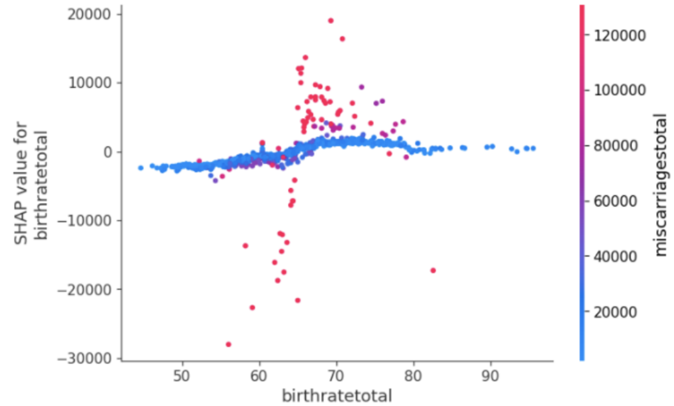

Fig. 5 SHAP values: miscarriages vs. birth rate. *Miscarriage totals are linked to subtle variations in birth rate predictions, suggesting disparities in healthcare access and maternal health outcomes even in populations with average birth rates.*

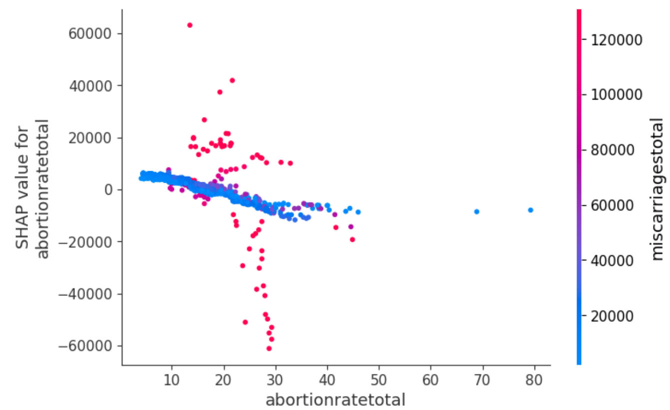

Fig. 6 SHAP values: miscarriages vs. abortion rate. *A negative relationship indicates that higher abortion rates reduce the feature's predictive importance. Clusters of high miscarriage totals at moderate abortion rates point to overlapping healthcare access issues.*

support, and postpartum assistance, particularly in underserved areas, can improve outcomes significantly. Collaborating with local organizations to provide holistic care can also help address the needs of vulnerable populations.

Finally, addressing the social determinants of health is essential for long-term change. Tackling root causes like poverty, lack of education, and inadequate healthcare infrastructure can reduce disparities in reproductive health outcomes. Partnerships between healthcare providers and social services can create integrated systems of care that address these underlying issues. By leveraging data-driven insights, advocacy groups and policymakers can create compelling narratives that drive systemic change, ensuring better health outcomes for all individuals. This highlights the SHAP[5] values for the year feature, with the color gradient representing the total number of miscarriages[15] (miscarriagetotal). The increasing SHAP values over time indicate that the influence of year on the model's predictions has grown. This trend could reflect improvements in data collection, changes in healthcare systems, or shifts in societal attitudes toward reproductive health. The concentration of high miscarriage totals (marked in red) in recent years might point to factors like delayed pregnancies, rising chronic health conditions, or greater awareness and reporting accuracy.

This graph in Fig. 4 underscores the importance of considering how historical and temporal trends impact reproductive health. For example, advancements in healthcare technologies or policies may have improved reporting and accessibility, but the increase in high-risk pregnancies due to lifestyle or medical factors also warrants attention. This examines the SHAP[5] values for birthratetotal, showing its relationship to birth rates and miscarriage[15] totals. The relatively flat distribution of SHAP values suggests that birthrate has a more limited direct impact on the model's predictions compared to year. However, clusters of red points (indicating higher miscarriage totals) near average birthrate levels suggest a nuanced relationship. This could indicate disparities in healthcare access, social or economic conditions, or other confounding factors that influence both birthrates and miscarriages.

This graph in Fig. 5 highlights the need to further explore systemic inequities affecting birth and miscarriage[15] rates. For example, communities with average birthrates may still face barriers to adequate prenatal care or education about reproductive health, contributing to higher miscarriage rates. This graph plots in Fig. 6 the SHAP[5] values for the feature abortionratetotal against the abortion[14] rate. The color gradient reflects the total number of miscarriages[15] (miscarriagetotal). The negative correlation between SHAP values and abortion rate suggests that higher abortion rates may reduce the feature's importance in the model's predictions. However, clusters of red points (high miscarriage totals) around moderate abortion rates highlight a

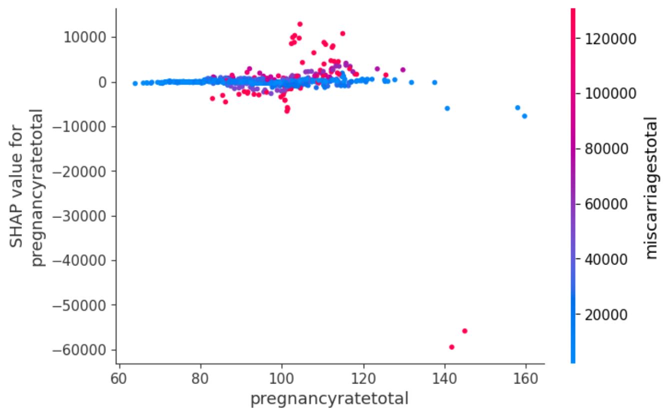

Fig. 7 SHAP values: miscarriages vs. pregnancy rate. *Pregnancy rate contributes consistently to model predictions, but clusters of higher miscarriage totals reveal underlying health disparities, particularly in prenatal care access and maternal health conditions.*

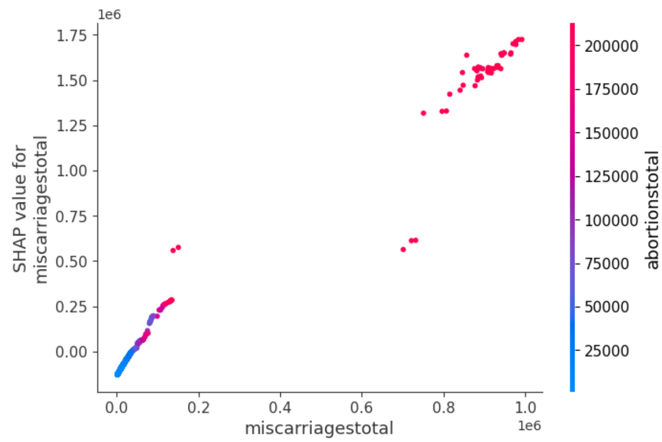

Fig. 8 SHAP values: miscarriages vs. abortion totals. *Miscarriage totals are highly predictive, with SHAP values increasing alongside miscarriage counts. This emphasizes the central role of miscarriage trends in shaping reproductive outcomes.*

potential overlap of factors influencing both abortions and miscarriages, such as healthcare access or societal norms regarding family planning.

This graph in Fig. 6 points to the need for nuanced analysis of how abortion [14] rates and miscarriage [15] trends intersect, focusing on improving healthcare systems that address both outcomes comprehensively. This graph in Fig. 7 illustrates the SHAP [5] values for pregnancyratetotal against pregnancy rates, again with miscarriage [15] totals as the color gradient. The relatively uniform SHAP values indicate that pregnancy rates contribute consistently to the model's predictions, regardless of fluctuations in the number of pregnancies. However, the concentration of red points around average pregnancy rates could suggest underlying stressors or risk factors that increase miscarriage totals even in regions or groups with typical pregnancy rates.

This insight highlights the importance of addressing underlying causes of miscarriages [15] , such as prenatal care quality or maternal health conditions, across diverse populations. The final graph in Fig. 8 shows a strong linear correlation between the SHAP [5] values and the miscarriagetotal feature, with a color gradient representing the total number of abortions (abortionstotal). The increasing SHAP values alongside miscarriage totals indicate that this feature is highly predictive in the model. High miscarriage totals (red points) are aligned with higher SHAP values, showing their dominant influence on the model's predictions.

This graph emphasizes the central role of miscarriage data in reproductive health models. It calls for targeted interventions in areas with high miscarriage rates, ensuring that affected individuals receive adequate healthcare, counseling, and preventive measures.

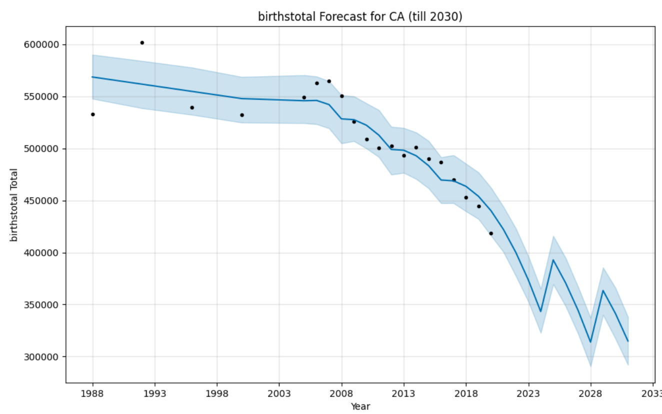

Fig. 9 Prophet forecast of California birth totals through 2030. *The forecast projects a continued decline in annual births, with oscillations between 2025 and 2030. The shaded area represents the uncertainty interval, which widens further into the future.*

Time Forecasting Model

The Prophet [6] forecasts for California and Texas consistently project long-term declines across births, abortions [14] , miscarriages [15] , and pregnancies through 2030. Although both states follow a downward trajectory, the patterns differ in magnitude and volatility. California's outcomes generally display smoother declines with modest late-decade rebounds, while Texas shows sharper oscillations, reflecting its demographic volatility, restrictive reproductive health policies, and uneven access to care.

In both states, birth totals are projected to decrease steadily, punctuated by fluctuations in the late 2020s. California shows relatively small oscillations, suggesting short-term rebounds that do not alter the overall downward trend. Texas, by con-

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	400021.740617	377411.750127	423138.538403
22	2022-12-31	373698.964945	352906.797660	396508.773335
23	2023-12-31	343239.674806	322827.765456	365187.714998
24	2024-12-31	392803.446705	369482.747719	415953.051165
25	2025-12-31	370648.060886	348315.502554	394658.391828
26	2026-12-31	344325.285215	321905.979107	366976.033373
27	2027-12-31	313865.995075	290699.020321	337192.433851
28	2028-12-31	363429.766975	340093.057902	385597.241360
29	2029-12-31	341274.381155	317029.154110	365953.450077
30	2030-12-31	314951.605484	292098.263388	338143.054441

Fig. 10 Numerical table of forecasted birth totals, 2021–2030. *The table summarizes Prophet's predictions, showing declining births with short-term rebounds around 2028–2029, reflecting possible sensitivity to economic and policy shifts.*

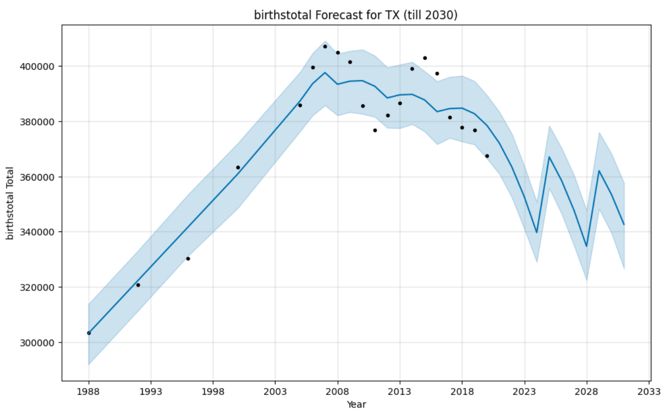

Fig. 11 Prophet forecast of Texas birth totals through 2030. *The forecast projects a gradual decline in annual births across Texas, with fluctuations between 2026–2029. The shaded region represents the 95% uncertainty interval, widening as the projection extends further into the future.*

trast, exhibits sharper swings, with temporary recoveries around 2027–2028 followed by renewed declines. These dynamics suggest that external shocks—such as economic cycles, healthcare access, or immigration flows—may more strongly affect fertility outcomes in Texas.

Forecasts mirror the decline in births, with intermittent rebounds late in the decade. California's trajectory reflects broader improvements in contraception, lower pregnancy rates, and demographic shifts such as delayed childbearing. Texas shows more volatility, where restrictive reproductive policies and disparities in healthcare access amplify fluctuations. These differences underscore how state-level policy environments directly shape reproductive outcomes.

Both states show a gradual decline with rebounds in the late 2020s, though California's trajectory is smoother while Texas experiences greater variability. Miscarriage[15] trends appear especially sensitive to maternal health factors, including delayed childbearing, chronic health conditions, and disparities in prenatal care. The widening confidence intervals highlight growing

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	363451.400518	352394.987993	375472.101253
22	2022-12-31	352652.196810	341054.816182	363850.567353
23	2023-12-31	339690.743539	329051.921258	350777.980693
24	2024-12-31	367082.178481	355798.438661	378402.369887
25	2025-12-31	358460.780577	346416.333981	370241.051182
26	2026-12-31	347661.576870	334881.770660	360402.108135
27	2027-12-31	334700.123599	322477.893045	347690.250793
28	2028-12-31	362091.558540	348256.968042	376038.290982
29	2029-12-31	353470.160637	339512.492258	368202.770945
30	2030-12-31	342670.956929	326666.053906	357669.435272

Fig. 12 Forecasted annual birth totals in Texas, 2021–2030. *Tabular summary of Prophet's predictions. While total births decline overall, short-term rebounds are visible around 2027–2028, suggesting sensitivity to external shocks such as policy shifts or economic changes.*

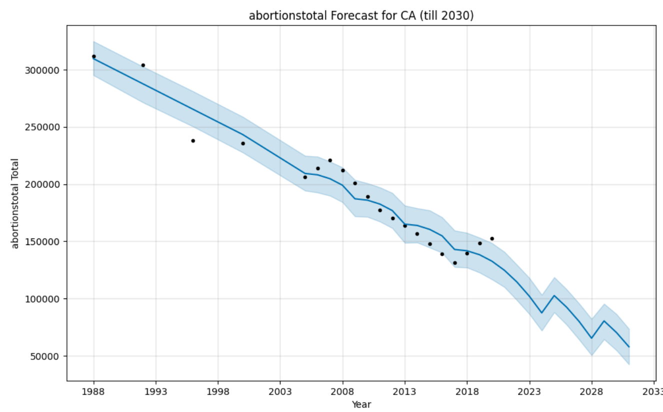

Fig. 13 Prophet forecast of California abortion totals through 2030. *The model projects a gradual decline in abortions, with minor fluctuations around 2025–2028. The shaded uncertainty interval widens further into the future, reflecting external policy and healthcare uncertainties.*

uncertainty tied to healthcare systems and demographic change.

Pregnancy totals are projected to decline steadily in both states, with modest rebounds in the late 2020s. California's declines are gradual and shaped by delayed family formation, economic pressures such as housing and childcare costs, and cultural shifts toward higher education and career prioritization. Texas shows sharper oscillations, influenced by restrictive reproductive health laws and uneven healthcare infrastructure. Immigration may buffer declines in Texas by sustaining a younger childbearing population, but policy barriers may offset these demographic advantages.

Synthesis of graphs

Taken together, the forecasts reveal a consistent long-term decline across fertility-related indicators in both states, with intermittent rebounds that do not alter the overall trajectory. California's trends are relatively stable, while Texas exhibits more volatility due to demographic growth, restrictive policies, and

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	114576.393805	98693.561313	129627.046541
22	2022-12-31	102172.744546	86589.330003	118101.094358
23	2023-12-31	87543.161876	72082.735594	103298.719332
24	2024-12-31	102642.120122	88058.549554	118694.772945
25	2025-12-31	92476.883942	77205.530053	108079.490287
26	2026-12-31	80073.234684	64242.434243	95780.439356
27	2027-12-31	65443.652013	50646.668468	82311.004105
28	2028-12-31	80542.610259	64532.757660	95536.391546
29	2029-12-31	70377.374080	54884.959039	86498.004297
30	2030-12-31	57973.724821	42599.842432	73627.539312

Fig. 14 Forecasted annual abortion totals in California, 2021–2030 *Tabular summary of predicted abortion counts. Declines continue overall, though temporary rebounds appear in the late 2020s, suggesting sensitivity to policy changes and healthcare access*

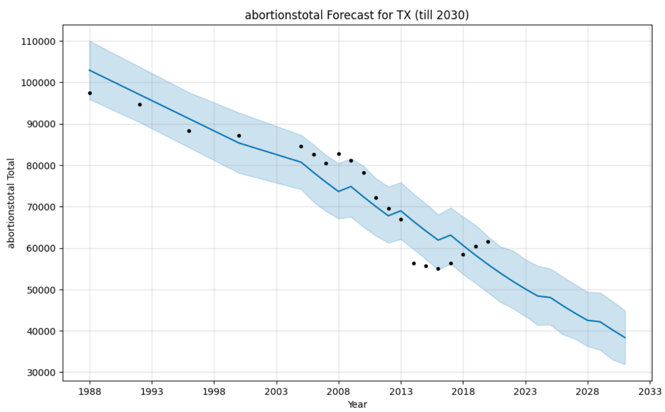

Fig. 15 Prophet forecast of Texas abortion totals through 2030. *The forecast shows overall declines in abortions across Texas, with short-term oscillations between 2026–2029. Policy restrictions and healthcare disparities may contribute to sharper fluctuations compared to California.*

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	51952.240086	45415.926199	59376.878120
22	2022-12-31	50109.533462	43528.764272	57247.118161
23	2023-12-31	48396.510561	41404.826360	55663.901866
24	2024-12-31	48055.555002	41469.098419	55009.172297
25	2025-12-31	46083.168825	39142.030321	53054.945528
26	2026-12-31	44240.462201	38045.261286	51190.120609
27	2027-12-31	42527.439300	36251.871167	49370.633956
28	2028-12-31	42186.483741	35391.703153	49223.817835
29	2029-12-31	40214.097564	33052.268180	47130.842970
30	2030-12-31	38371.390940	31910.780924	44945.558491

Fig. 16 Forecasted annual abortion totals in Texas, 2021–2030 *Tabular summary of projected abortion counts. While totals trend downward, the late 2020s display intermittent rebounds, highlighting Texas's sensitivity to demographic and policy shocks.*

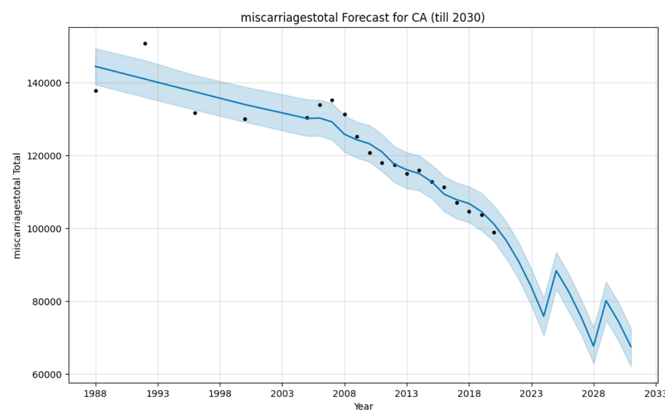

Fig. 17 Prophet forecast of California miscarriage totals through 2030. *Forecasted miscarriages show a steady long-term decline, with fluctuations around 2026–2029. The widening uncertainty interval suggests demographic and healthcare-related variability.*

healthcare inequities. Across both states, widening uncertainty intervals underscore the influence of unpredictable external factors, including economic recessions [17] , policy shifts, and public health crises. These findings highlight that while structural demographic shifts drive the overall decline, state-specific policy contexts amplify or moderate fluctuations.

Prophet Evaluation

To evaluate the accuracy of the Prophet [6] forecasting model, its performance was compared against a simple linear regression baseline using two widely accepted time-series error metrics: Root Mean Squared Error (RMSE) [8] and Mean Absolute Percentage Error (MAPE) [9] . Prophet achieved an RMSE of 6,231.41 and a MAPE of 0.83%, while linear regression produced a much higher RMSE of 49,041.27 and MAPE of 10.13%. These results indicate that Prophet's predictions were very close to the actual fertility counts, with deviations averaging less than 1% relative to the observed values. In contrast, linear regression struggled to capture the dynamics of the data, resulting in large errors that reflect its inability to model nonlinear trends and seasonal variation.

The substantial gap in performance highlights Prophet's [6] strength as a time-series forecasting tool [1] , particularly for demographic datasets where fertility outcomes are shaped by both long-term trends and fluctuations in response to policy and economic conditions. Prophet's capacity to incorporate seasonality and uncertainty intervals enables it to outperform simpler models that assume linear change over time. The validation results reinforce that Prophet provides a reliable forecast of California's declining fertility trends, supporting its use as a robust model for anticipating demographic shifts and informing healthcare and policy planning.

To validate the accuracy of the Prophet [6] model in Texas, forecasts were again compared against a linear regression baseline using RMSE [8] and MAPE [9] . Prophet achieved an RMSE of 8,625.96 and a MAPE of 1.84%, whereas linear regression performed considerably worse, with an RMSE of 42,771.15 and a MAPE of 10.68%. These results show that Prophet was able to

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	90794.392030	85932.485534	95969.072985
22	2022-12-31	83886.593117	78802.852629	88832.584119
23	2023-12-31	75824.298584	70485.070061	80849.401703
24	2024-12-31	88326.732095	83328.105402	93369.398206
25	2025-12-31	82581.493397	77151.239563	87435.613909
26	2026-12-31	75673.694484	70821.132404	80532.027948
27	2027-12-31	67611.399950	62838.663523	72691.848759
28	2028-12-31	80113.833462	74709.213989	85270.502436
29	2029-12-31	74368.594763	69062.117605	79623.604568
30	2030-12-31	67460.795850	62058.137813	72472.184672

Fig. 18 Forecasted annual miscarriage totals in California, 2021–2030 *Tabular summary of predicted miscarriage totals. Projections indicate continued declines, but late-decade rebounds may reflect changing maternal health conditions or improved reporting*

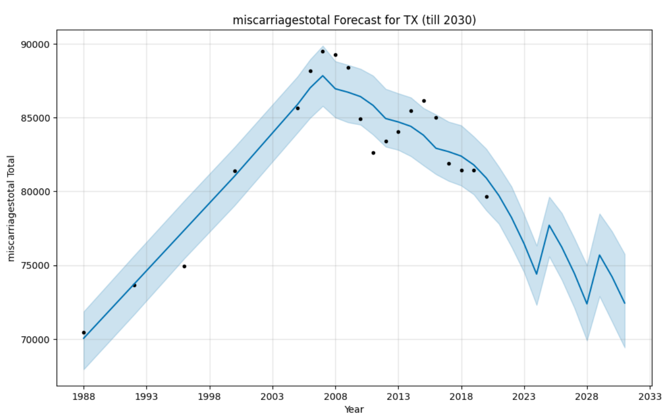

Fig. 19 Prophet forecast of Texas miscarriage totals through 2030. *The model predicts a general decline in miscarriages, with short-term increases around 2027–2028. The broader confidence interval suggests stronger susceptibility to healthcare and policy variability than California.*

closely reproduce the observed fertility patterns in Texas, with average prediction errors under 2% of the actual values. In contrast, the linear regression model significantly misrepresented the data, reflecting its limitations in capturing nonlinear fertility dynamics.

The evaluation underscores Prophet's[6] superior ability to handle state-level fertility time series compared to simple baselines. Although Prophet's error rates in Texas were slightly higher than those observed for California, they remain low enough to ensure that forecasts provide meaningful insights into demographic change. By capturing fluctuations and long-term decline more effectively than linear regression, Prophet offers a reliable approach to modeling future fertility trends in Texas, highlighting its robustness across different states with distinct demographic and policy contexts.

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	78232.765302	76248.977304	80325.653031
22	2022-12-31	76457.862236	74526.499378	78417.177602
23	2023-12-31	74391.653714	72297.885619	76325.487801
24	2024-12-31	77699.679964	75584.836503	79626.467472
25	2025-12-31	76218.081959	74005.418053	78526.378177
26	2026-12-31	74443.178893	72109.266434	76816.272265
27	2027-12-31	72376.970371	69898.498682	74984.701394
28	2028-12-31	75684.996621	72889.278116	78488.026820
29	2029-12-31	74203.398616	71162.963780	77275.235207
30	2030-12-31	72428.495551	69415.062130	75748.599551

Fig. 20 Forecasted annual miscarriage totals in Texas, 2021–2030 *Tabular summary of projected miscarriage totals. Declines dominate the forecast, though late-decade rebounds point to potential fluctuations in maternal health outcomes*

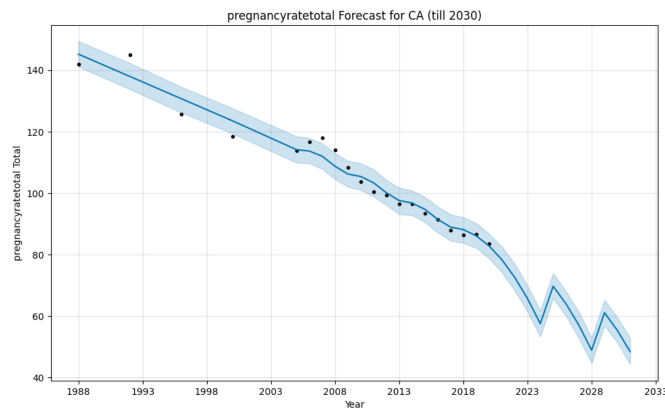

Fig. 21 Prophet forecast of California pregnancy totals through 2030. *Pregnancy totals are forecasted to decline steadily, with small oscillations after 2026. The shaded interval highlights growing long-term uncertainty.*

Discussion

This study combined machine learning and time-series forecasting[1] to analyze fertility dynamics in California and Texas from 1973 to 2020 and to project future birth totals through 2030. The Prophet[6] model revealed sustained long-term declines in fertility across both states, punctuated by fluctuations in the mid- to late 2020s that suggest temporary rebounds followed by continued decreases. California's projections indicated relatively modest oscillations, while Texas displayed sharper variability, reflecting the state's distinctive demographic growth, immigration dynamics, and restrictive reproductive policy environment.

Beyond forecasting, the integration of SHAP[5] analysis with XGBoost[7] regression identified miscarriage[15] totals, abortion[14] access, and state-level differences as the most influential predictors of fertility outcomes. These results emphasize how reproductive health trends are not only demographic in nature but also deeply intertwined with access to care and the sociopolitical landscape. The comparison between California and Texas underscores this point: while both states share a general downward

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	72.613523	68.272707	77.041251
22	2022-12-31	65.677657	61.531518	69.793090
23	2023-12-31	57.530652	53.240754	61.776634
24	2024-12-31	69.702925	65.849103	73.936807
25	2025-12-31	63.986225	59.985155	67.965433
26	2026-12-31	57.050358	52.790325	61.386678
27	2027-12-31	48.903354	44.711475	52.951555
28	2028-12-31	61.075626	56.910966	65.246655
29	2029-12-31	55.358926	51.442154	59.497438
30	2030-12-31	48.423059	44.280460	52.974532

Fig. 22 Forecasted annual pregnancy totals in California, 2021–2030 *Tabular summary of predicted pregnancy totals. Projections show steady declines, with slight rebounds around 2028–2029 reflecting socioeconomic or healthcare shifts.*

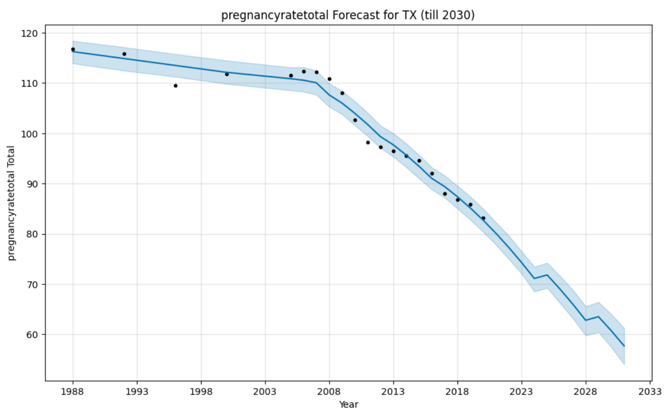

Fig. 23 Prophet forecast of Texas pregnancy totals through 2030. *Pregnancy totals in Texas are forecasted to decline, with more pronounced fluctuations than California, particularly in 2026–2029.*

	ds	yhat	yhat_lower	yhat_upper
21	2021-12-31	77.317922	75.008581	79.654461
22	2022-12-31	74.314596	72.094244	76.534324
23	2023-12-31	71.118788	68.525051	73.461776
24	2024-12-31	71.826183	69.242715	74.229994
25	2025-12-31	69.016607	66.216674	71.634061
26	2026-12-31	66.013281	63.197770	68.839868
27	2027-12-31	62.817473	59.791267	65.590750
28	2028-12-31	63.524868	60.447806	66.432918
29	2029-12-31	60.715292	57.439326	64.019214
30	2030-12-31	57.711966	54.049551	61.236884

Fig. 24 Forecasted annual pregnancy totals in Texas, 2021–2030 *Tabular summary of projected pregnancy totals. While long-term declines dominate, short-term rebounds underscore sensitivity to state-level policy and demographic change.*

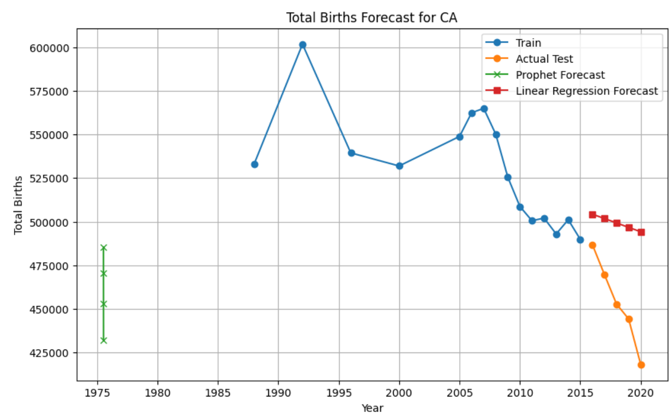

Fig. 25 Prophet vs. Linear Regression forecast accuracy in California. *Comparison of observed vs. predicted births highlights Prophet's superior performance, with errors consistently smaller than linear regression. Prophet's ability to capture nonlinear trends improves accuracy over traditional statistical baselines.*

fertility trajectory, the drivers and magnitude of decline vary according to policy context and healthcare availability.

The methodological contribution of this study lies in demonstrating how forecasting accuracy can be paired with interpretability. Prophet[6] outperformed linear regression in both states, with error rates under 2% of actual values, while SHAP[5] provided transparent explanations of model predictions. Taken together, these approaches illustrate how interpretable AI can enrich demographic forecasting, supporting policymakers, healthcare providers, and researchers in anticipating fertility shifts and planning responsive interventions.

The study successfully met its objectives by generating accurate forecasts, identifying influential predictors, and demonstrating the utility of explainable AI for public health research. Nevertheless, limitations remain. The reliance on state-level aggregated data constrains generalizability, and long-term projections are inherently uncertain, subject to external shocks such as recessions[17] , legislative changes, or public health crises. Moreover, while SHAP[5] illuminates associations, it does not establish causality, and results must therefore be interpreted with caution. Future research should expand to multi-state or national datasets, incorporate socioeconomic and healthcare access variables, and explore hybrid models that combine demographic theory with advanced machine learning. Such approaches could further strengthen the balance between predictive power and interpretability. Overall, this study demonstrates the potential of interpretable AI to deepen our understanding of fertility decline. As reproductive health in the United States continues to be shaped by evolving policies, economic conditions, and cultural shifts, transparent, data-driven forecasting tools[1] like Prophet[6] —combined with explainable methods such as SHAP[17] —offer critical guidance for equitable healthcare planning, resource allocation, and policy design.


```
Prophet RMSE: 6231.41
Prophet MAPE: 0.83%
Linear Regression RMSE: 49041.27
Linear Regression MAPE: 10.13%
```

Fig. 26 Forecast error comparison in California. *Error metrics (RMSE and MAPE) demonstrate Prophet's advantage over linear regression, achieving an RMSE of 6,231.41 compared to 49,041.27 for linear regression. Prophet deviates by less than 1% on average from observed fertility outcomes.*

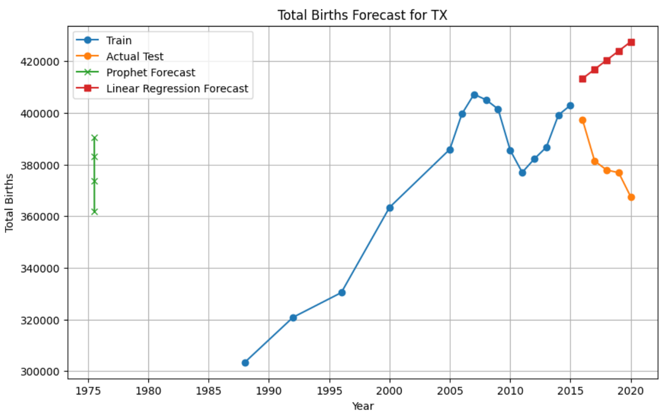

Fig. 27 Prophet vs. Linear Regression forecast accuracy in Texas. *Observed vs. predicted births show Prophet's closer alignment with actual fertility patterns in Texas, while linear regression produces greater deviations and fails to capture short-term oscillations.*

```
Prophet RMSE: 8625.96
Prophet MAPE: 1.84%
Linear Regression RMSE: 42771.15
Linear Regression MAPE: 10.68%
```

Fig. 28 Forecast error comparison in Texas. *Evaluation metrics show Prophet outperforming linear regression (RMSE: 8,625.96 vs. 42,771.15; MAPE: 1.84% vs. 10.68%), confirming the model's reliability in a state with different demographic and policy contexts.*

References

1 G. Livingston, *Why is the U.S. fertility rate falling?*, Pew Research Center, 2019.

2 S. Taylor and B. Letham, *The American Statistician*, 2018, **72**, 37–45.

3 R. Wade, *R. Wade*, Oyez, 1973, p. 410 113.

4 *Casey*, 1992, **505 U.S. 833**, year.

5 S. Lundberg and S.-I. Lee, *Advances in Neural Information Processing Systems (NeurIPS*, 2017.

6 R. Hyndman and G. Athanasopoulos, *Forecasting: Principles and practice*, OTexts, 3rd edn, 2021.

7 T. Chen and C. Guestrin, Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, p. 785–794.

8 U. Illinois Urbana-Champaign, *Root mean square error (RMSE) – Statistics with Python*, Discovery Partners Institute.

9 *Scikit-learn,developers*, https://scikit-learn.org/stable/modules/generated/sklearn.metrics.mean_absolute_percentage_error.html.

10 O.S.F., *Fertility rate measures by state and year (1973–2020*, Open Science Framework, 2020.

11 *Centers for Disease Control and Prevention*, 2023, https://www.cdc.gov/nchs/nvss.

12 *National Center for Health Statistics*, 2020, https://www.cdc.gov/nchs/data/nvsr/nvsr70/nvsr70-17.pdf.

13 B. Hamilton, J. Martin, M. Osterman and L. Rossen, *Births: Provisional data for 2021*, National Vital Statistics System, 2022.

14 G. Institute, *State abortion policy landscape*, 2023, https://www.guttmacher.org/state-policy.

15 L. Rossen, K. Ahrens and A. Branum, *Paediatric and Perinatal Epidemiology*, 2018, **32**, 19–29.

16 E. Petersen, N. Davis, D. Goodman, S. Cox, C. Syverson, K. Seed and W. Barfield, *MMWR Morbidity and Mortality Weekly Report*, 2019, **68**, 762–765.

17 S. Morgan, E. Cumberworth and C. Wimer, *The Great Recession*, 2011, p. 220–245.