A Semi-Markov Model of Sequential Road Safety Legislation and Crash Fatalities in Nigeria

Abstract

Road traffic accidents are still a huge problem for public health in Nigeria, and they cause a lot of injuries, disabilities, and deaths. This study utilized a Semi-Markov Process (SMP) model to evaluate the effectiveness of various road safety policy interventions by simulating transitions among five states: S_0 (No major national policy), transitioning with certainty to S_1 (Seatbelt law enforced in 2003), then to S_2 (plus Speed Limiter enforcement in 2017), followed by S_3 (plus Driving School Standardization Program in 2018), and ultimately to S_4 (plus FRSC Mobile App and NACRIS introduced in 2024). The transition probabilities and mean waiting times for each state were derived from actual data. The study found that the average stay period was 7.2 years, which was what the SMP model said it would be (7.19 years). The estimated first passage time to mortality reduction (S_4) was highest from the baseline state S_0 (15.9 units) and went down steadily across S_1 (13.3 units), S_2 (7.9 units), and S_3 (6.9 units). This illustrates that modifying how we enforce speed limits makes it easier to meet our goals of lowering deaths. There was also a five-year forecast for road traffic mortality between 2025 and 2029. This demonstrated that the number of deaths might alter, and if no new policy is put in place, it could be anywhere from 5,296 to 5,547. These results support the idea that legislation should be the most important part of road safety programs, especially when it comes to speed limits and strict enforcement. The Semi-Markov framework has been beneficial for simulating the dynamics of road safety and can assist policymakers to make decisions that will minimize the number of deaths caused by road traffic crashes. Over time, improving Nigeria's road safety measures in various ways can have a huge effect on the country's traffic challenges.

Keywords: Semi-Markov model, Fatalities, Sojourn times, Nigeria, Policies

Introduction

Road traffic injuries and fatalities remain a significant public health issue globally, particularly in low- and middle-income countries (LMICs) such as Nigeria. More than 1.19 million people die each year in road traffic accidents, according to the World Health Organization (2023). With 26.6 deaths per 100,000 people, Africa has the highest death rate from these accidents. Nigeria has a rapidly rising population and transportation infrastructure that is still being built. This makes road traffic crashes (RTCs) happen more often than they should. The Federal Road Safety Corps (FRSC) was created in 1988 and has made several policy measures to try to minimize the incidence of deaths on the road. These include making seatbelts mandatory (2003), deploying speed-limiting devices (2016), modifying the way people receive their driver's licenses, sponsoring anti-drunk driving campaigns, and using mobile courts to police traffic regulations (FRSC, 2020). However, there has not been much research on how these wide and robust policy initiatives work together or one after the other. Most of the studies that look at Nigeria's road safety laws are either cross-sectional or focused on specific interventions. They examine factors such as compliance levels or pre- and post-policy outcomes (Uzondu et al., 2022; Ismaila & Akanbi, 2010). Although these studies provide valuable insights, they often overlook the temporal interactions of laws and the stochastic nature of accident dynamics and fatalities. They also tend to treat laws as independent events, without recognizing that their effects can build upon one another, interact, or diminish over time. Elvik (2016) demonstrated through meta-analysis that the effects of successive road safety regulations are not merely additive also can display synergistic or delayed outcomes, which can only be clarified through dynamic modeling frameworks. In high-income countries, advanced statistical techniques such as time-series models (Yusria, 2017), Bayesian change-point models (Wang & Abdel-Aty, 2015), and Markov decision processes (Ma et al., 2020) have been used to study road safety interventions. However, the use of semi-Markov processes, which extend ordinary Markov models by incorporating variable sojourn (holding) times, remains rare, particularly in sub-Saharan Africa. A Semi-Markov model (SMM) is particularly well-suited for this type of analysis because it explicitly accounts for state-dependent transitions and variable sojourn times between policy phases, rather than assuming uniform or regular time intervals. In contrast, time-series models such as ARIMA assume stationarity and continuous temporal dependence, which may not capture the discrete, event-driven nature of policy interventions (Limnios & Oprisan, 2012). SMMs allow the modeling of both transition probabilities and duration of policy effects, providing a richer picture of how long each policy environment remains effective before another regulation is introduced (Barbu & Limnios, 2008). This is crucial in safety policy evaluation, where impacts often unfold irregularly and interventions occur sporadically rather than periodically. Furthermore, Semi-Markov frameworks have been shown to outperform classical time-series methods in capturing non-Markovian behavior and long-term dependencies in systems influenced by policy-induced regime changes (Anderson & Goodman, 1957; Guo, 2009). Thus, the Semi-Markov process provides a more realistic stochastic representation of Nigeria's sequential road safety policies and their cumulative effects on crash fatalities over time. Although numerous Nigerian studies have assessed the effects of individual road safety legislations (Olumide & Owoaje, 2016; Oluwadiya et al., 2015), none have systematically evaluated their aggregate, time-dependent impacts using a stochastic modeling framework that leverages actual fatality data. This represents a significant research gap, as the timeline of policy implementation in Nigeria is non-linear and characterized by variable enforcement intensity. Laws often take different durations to produce measurable effects, and their influences can be interdependent or delayed. This study seeks to address this gap by employing a semi-Markovian modeling approach to assess the cumulative impact of successive FRSC road safety interventions on crash fatalities in Nigeria. This study is set to conceptualize each policy environment as a state and each new intervention as a transition, this approach will account for the stochastic nature of accidents and the irregular timing of policy implementations. Modeling the sojourn times of each state allows for consideration of the varying time lags between policy enactment and observable outcomes. Ultimately, this framework offers both a methodological innovation for road safety research in LMICs and a practical decision-making tool for Nigerian policymakers seeking evidence-based, time-sensitive traffic safety strategies.

Methodology

Study Design

This is a retrospective, policy impact modeling study using a discrete-time semi-Markov process. The semi-Markov framework allows for modeling time-dependent transitions between policy states and captures the sojourn time (i.e., duration) a state persists before transitioning to the next. This is crucial, given that policies often remain in effect concurrently, and their impact unfolds over time.

The study period spans from 2000 to 2024, covering multiple major road safety policies including:

- Mandatory seatbelt enforcement (2003),
- Speed limiter policy (2017), etc

Data Source

Data is collected from the Annual FRSC Road Traffic Crash Reports(2024).

Model and Definition

Let the road safety evolution be modeled as a semi-Markov process (SMP), where transitions occur through a series of policy states, each with variable sojourn time.

State Definitions and Transition Matrix

Define the system as having five states:

- S_0: No major national policy
- S_1: Seatbelt law enforced (2003)

- S_2: + Speed limiter enforcement (2017)
- S_3: + DSSP (2018)
- S_4: + FRSC Mobile App & NACRIS (2024) — Absorbing state

The transition matrix is:

$$P = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

This represents a unidirectional process with S_4 as the absorbing state. This may facilitates tractable estimation of sojourn times and expected fatalities. However, the deterministic transition, may underestimate stochastic variability and the nuanced dynamics of policy interaction.

Mathematical Formulation of SMP

Let:

- $X(t)$: state occupied at time t
- J_n: state after the n-th transition
- T_n: time of the n-th transition

Then:

$$X(t) = J_n \quad \text{for } T_n \leq t < T_{n+1} \tag{2}$$

The semi-Markov kernel is:

$$Q_{ij}(t) = \mathbb{P}(J_{n+1} = j, T_{n+1} - T_n \leq t \mid J_n = i) \tag{3}$$

The embedded Markov chain has transition probability:

$$p_{ij} = \lim_{t \to \infty} Q_{ij}(t) \tag{4}$$

The sojourn time distribution $S_i \sim F_i(t)$ satisfies:

$$F_i(t) = \mathbb{P}(S_i \leq t) = \sum_{j \neq i} Q_{ij}(t) \tag{5}$$

Sojourn Time Estimation (Exponential Distribution)

Assuming exponential sojourn times in each state, we model:

$$S_i \sim \text{Exponential}(\lambda_i)$$

The probability density function is:

$$f_i(t) = \lambda_i e^{-\lambda_i t}, \quad t \geq 0 \tag{6}$$

The cumulative distribution function is:

$$F_i(t) = 1 - e^{-\lambda_i t} \tag{7}$$

The mean sojourn time is:

$$\mathbb{E}[S_i] = \frac{1}{\lambda_i} \tag{8}$$

Parameter Estimation

Let the observed sojourn times in state i be $\{s_{i1}, s_{i2}, \ldots, s_{in_i}\}$. The log-likelihood for the exponential distribution is:

$$\log L(\lambda_i) = n_i \log \lambda_i - \lambda_i \sum_{k=1}^{n_i} s_{ik} \tag{9}$$

The MLE is obtained by setting derivative to zero:

$$\frac{d}{d\lambda_i} \log L = \frac{n_i}{\lambda_i} - \sum s_{ik} = 0 \Rightarrow \hat{\lambda}_i = \frac{n_i}{\sum s_{ik}}$$

First Passage Time to Absorbing State

Let m_i be the expected first passage time from state i to absorbing state S_4. Then:

$$m_i = \mathbb{E}[S_i] + \sum_{j \neq i} p_{ij} m_j \tag{10}$$

Given the deterministic chain $p_{i,i+1} = 1$, we compute recursively:

$$\begin{aligned} m_4 &= 0 \\ m_3 &= \mathbb{E}[S_3] + m_4 \\ m_2 &= \mathbb{E}[S_2] + m_3 \\ m_1 &= \mathbb{E}[S_1] + m_2 \\ m_0 &= \mathbb{E}[S_0] + m_1 \end{aligned} \tag{11}$$

Forecasting Road Traffic Fatalities

Let Y_t be the number of fatalities in year t, and $S_t \in \{0, 1, 2, 3, 4\}$ be the state index at time t. We model fatalities via:

$$Y_t = f(S_t; \theta) + \varepsilon_t \tag{12}$$

Where:

- $\theta = (\mu_0, \mu_1, \mu_2, \mu_3, \mu_4)$: state-specific mean fatalities
- $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$: Gaussian error

Under deterministic transition:

$$\hat{Y}_{t+1} = \mu_{i+1} \tag{13}$$

Forecast interval at 95% confidence:

$$\hat{Y}_{t+1} \pm z_{\alpha/2} \cdot \hat{\sigma} \tag{14}$$

Model Evaluation
Model fit is evaluated using:

- **AIC**: for comparing candidate sojourn distributions
- **KS test**: to assess goodness of fit between empirical and theoretical sojourn distributions.

Time Plot

Figure 1 shows the number of people who died in RTC in Nigeria between 2000 and 2024. A lot of fatalities were recorded at first, and the most deaths were in 2001, when about 10,000 individuals died. By 2005, deaths had dropped below 5,000. The trend was volatile between 2006 and 2016. The 2017 speed limiter policy saw modest decline. Further interventions in 2018 and 2024 had varied impacts.

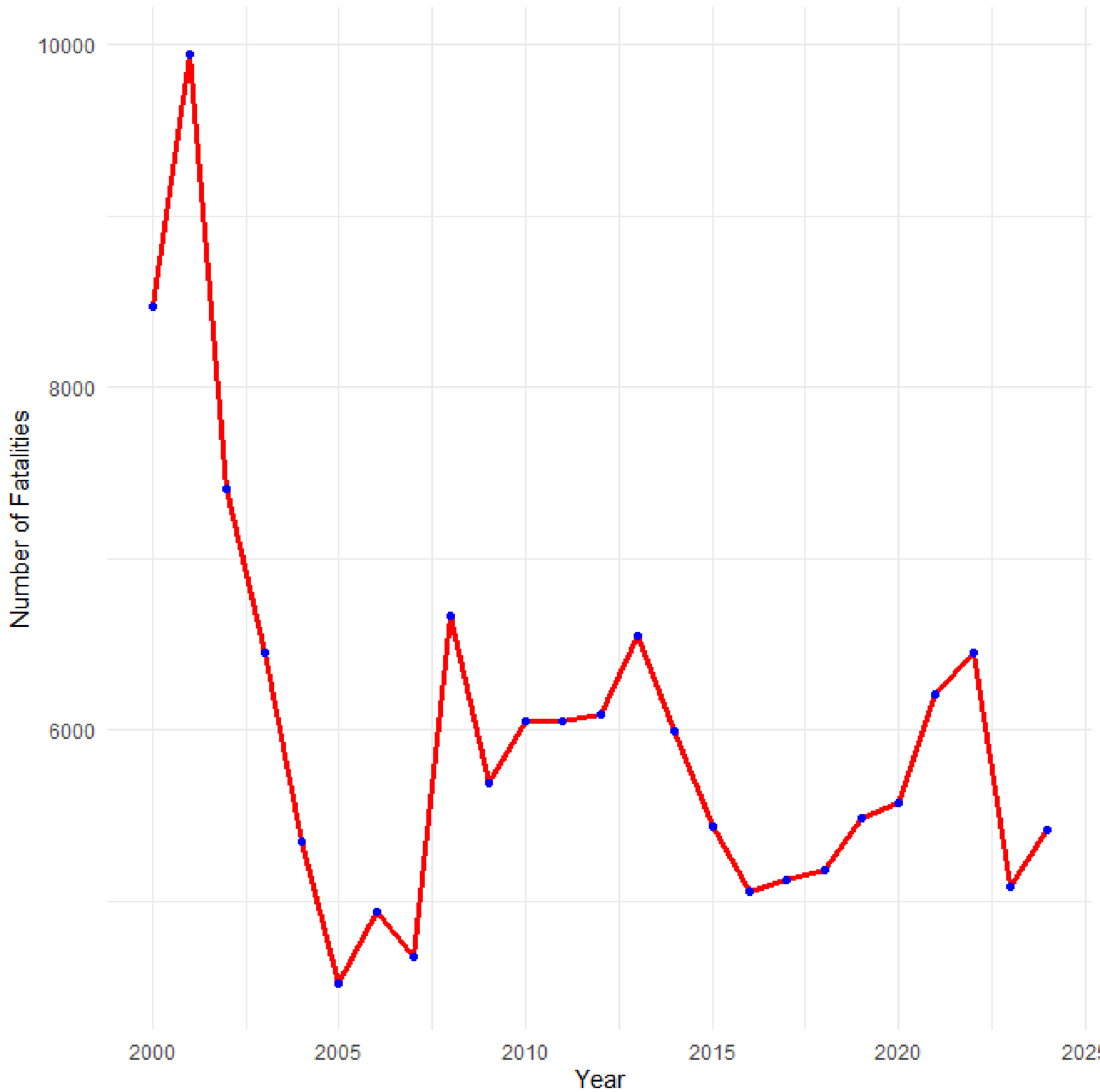

Figure 1: Trend of Traffic Fatalities (2000–2024)

Descriptive Statistics

The road traffic crash (RTC) fatalities series had a mean of 5995 (SD = 1,202.9), with values ranging from 4,519 to 9,946.

Table 1: Summary of RTC fatalities Series

Mean	Median	St Deviation	Minimum	Maximum	
5995	5693	1203	4519	2.27	9946

Transition Probability Matrix

The transition probability matrix shows a one-way, step-by-step movement through five states (S_0 to S_4). Each state is a crucial phase in Nigeria's national road safety strategy. The matrix makes it clear that the process will go from state S_0 (No major national policy) to state S_1 (Seatbelt regulation enacted in 2003). Next, it goes to state S_2 (with the Speed Limiter enforcement in 2017), then to state S_3 (with the Driving School Standardization Program in 2018), and eventually to state S_4 (with the FRSC Mobile App NACRIS released in 2024), which is an absorbing state. This framework explains how road safety measures have changed over time, which makes it feasible to figure out how long each phase of the policy lasts.

Table 2: Transition Probability Matrix

Policy	S_0	S_1	S_2	S_3	S_4
S_0	0	1	0	0	0
S_1	0	0	1	0	0
S_2	0	0	0	1	0
S_3	0	0	0	0	1
S_4	0	0	0	0	1

Sojourn Time Distribution

Among the four candidate distributions fitted to the sojourn time data, the exponential distribution emerged as the most efficient based on the lowest AIC value (31.74), indicating the best balance between model simplicity and goodness-of-fit. The estimated rate parameter for exponential model is 0.139

Table 3: Sojourn Time Distribution Parameters

Distribution	Shape	Scale/Rate	Meanlog	Sdlog	AIC
Exponential	-	0.139(0.06)	-	-	31.74
Weibull	1.211(0.451)	7.66(2.98)	-	-	33.49
Gamma	1.287(0.732)	0.179(0.124)	-	-	33.55
Lognormal	-	-	1.538(0.465)	1.04(0.329)	33.96

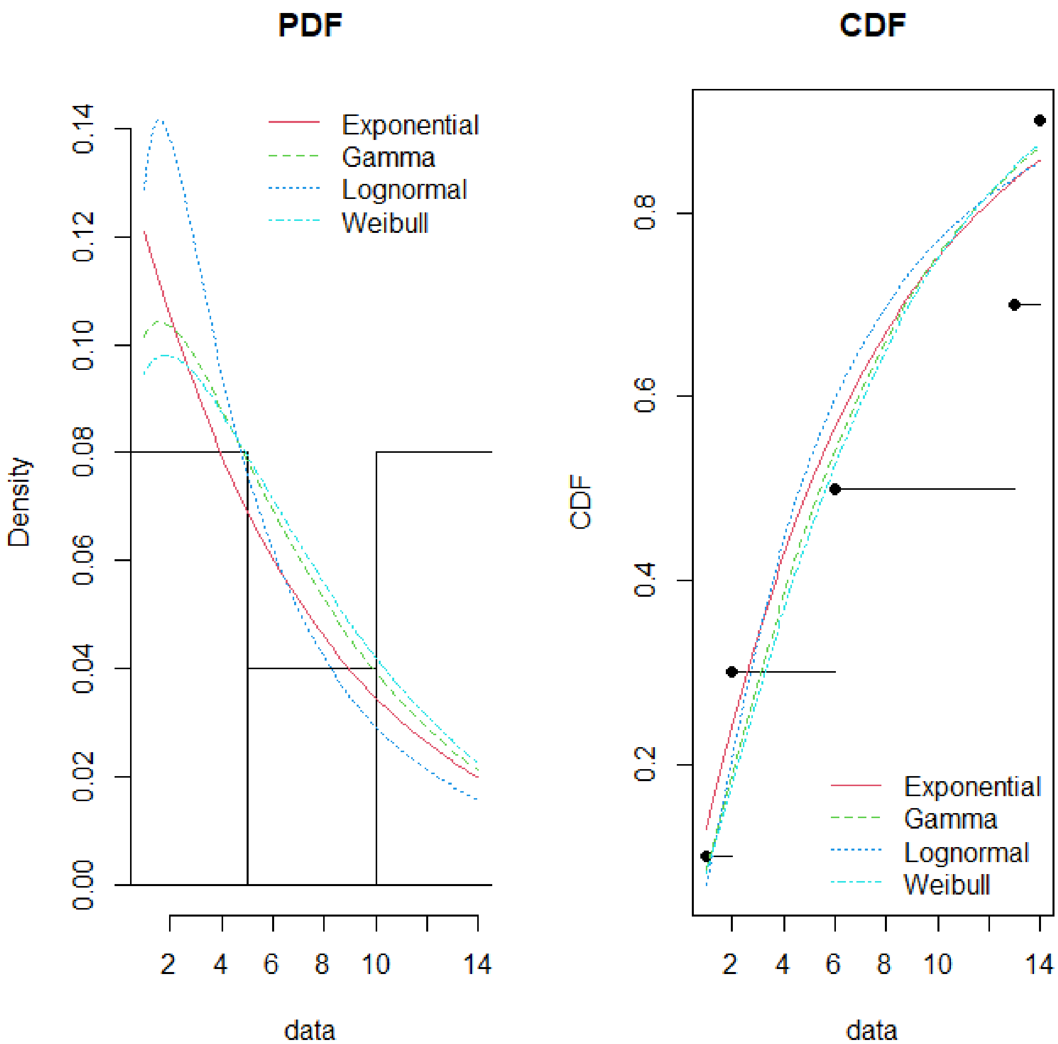

Figure 2: Probability Distribution of Sojourn Times

Summary Statistics

The simulation reproduces the empirical characteristics of policy durations quite well, validating the model structure.

Table 4: Summary of Observed vs Simulated Sojourn Times

	Mean	SD
Observed	7.2	6.05
Simulated	7.19	3.95

Expected First passage time to Absorption

The expected first passage times to the absorbing state S_4 from each transient state were computed. The results showed that the highest expected time to reach s4 was from state S_0, with a value of 15.9 years. This indicates that starting from S_0, the process takes the longest average time to reach the final state. From state S_1, the expected time reduced to 13.3 years, while from S_2 and S_3, the values were 7.9 and 6.9 years, respectively. This trend reflects a gradual decrease in expected time as the process progresses from S_0 to S_3, suggesting that states closer to S_4 require fewer transitions or face fewer delays in reaching the final outcome.

Table 5: Time to Absorption

State	EFPT
S_0	15.9
S_1	13.3
S_2	7.9
S_3	6.9

Kolmogorov-Smirnov Test

Table 4 presents the results of the Kolmogorov-Smirnov (KS) test conducted to evaluate whether the distribution of simulated policies durations matches that of the observed. The KS statistic was D= 0.20 with p-value of 1.0, showing no statistically significant difference between the two distributions. This suggests that the Semi-Markov model is well-calibrated and accurately reproduces the empirical distribution of Sojourn durations.

Table 6: KS Test Results

Data	D	p-value
Observed vs Simulated	0.2	1.0

Forecasting

The five-year forecast for road traffic fatalities from 2025 to 2029 shows fluctuations in projected deaths, with values ranging from 5,296 to 5,547 if no new policy is introduced. The highest number of fatalities is expected in 2029 (5,547), while the lowest is in 2027 (5,296). Across the forecast period, the 95% confidence interval remains consistent, with lower and upper bounds of 5,277 and 5,566 respectively, indicating moderate uncertainty around the predictions.

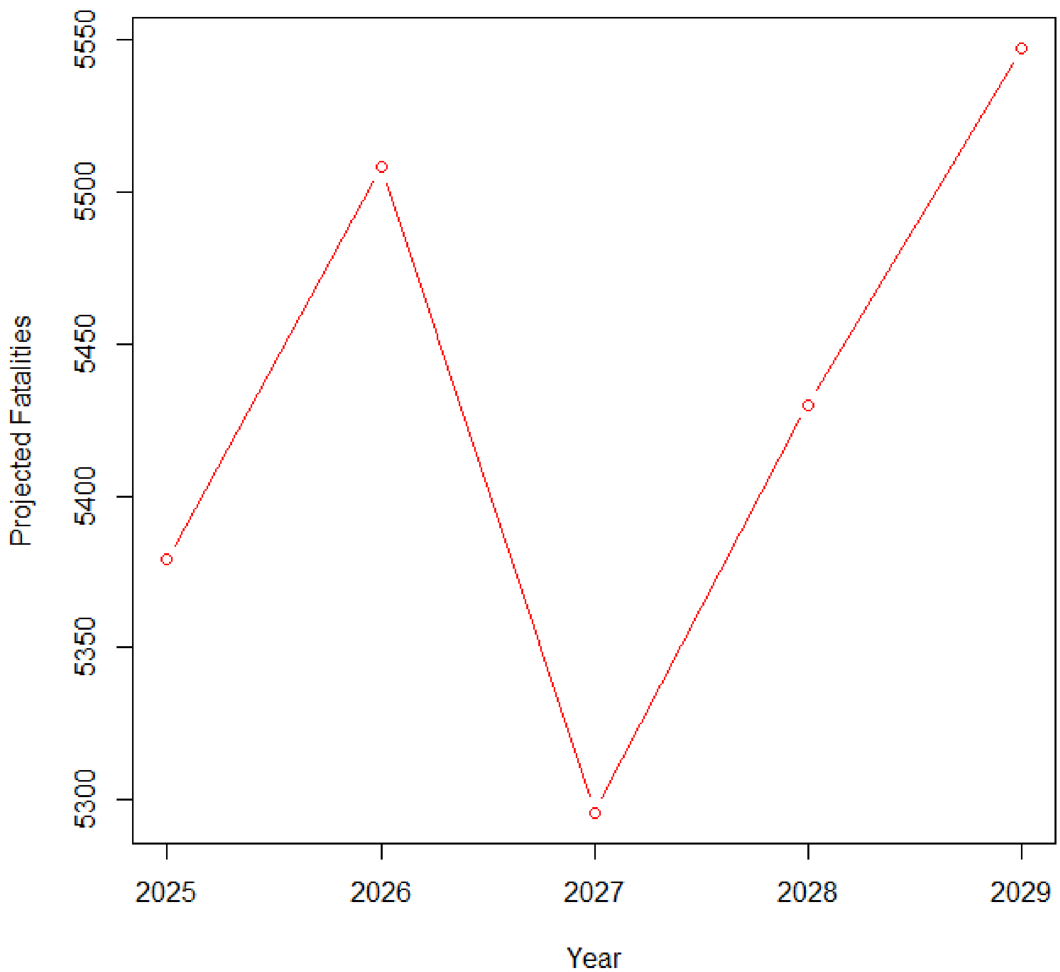

Figure 3: Forecast of Road Traffic Crash Fatalities (2025–2029)

Discussion of Findings

The Semi Markov analysis indicates that Nigeria's incremental implementation of road safety policies; seat belt law (2003), speed limiter enforcement (2016), driving school standardization (2018), and the FRSC mobile app/NACRIS (2024) aligns chronologically with the observed trend in fatalities. The stochastic model's remarkable replication of empirical sojourn times (mean 7.2 years) and its close match in simulated durations (mean 7.19 years) reveal a robust description of policy dynamics. The exponential distribution's superior fit (AIC = 31.74) indicates that the decline rate in fatalities post-policy enactment operates in a memoryless fashion, demonstrating abrupt policy effects succeeded by relative stability, a trend corroborated by Ismaila & Akanbi

(2010), who documented significant decreases following seat belt enforcement in Nigeria. The KS test (D=0.20, p=1) shows that there is no significant difference, which supports the SMP's use of temporal durations in policy state transitions. Forecasts for fatalities from 2025 to 2029 indicate a slight variation, ranging from 5,296 to 5,547, accompanied with consistent confidence intervals. These numbers match what was expected based on actual life, if no new policies are put in place. The peak in 2029 makes sense because the NACRIS app isn't being used as much yet and law enforcement is becoming more digital. The results show how important it is to follow the rules and enforce them. FRSC claims that just 187,000 cars had speed limiters installed as of early 2025. This is less than 100% nationwide coverage (Gift, 2025). FRSC indicated that the gadget might cut down on accidents by 70%, although the seatbelt law from 2003 had a similar effect over the world, with mandatory seatbelt laws usually leading to 30–50% fewer accidents. Notably, qualitative reviews pointed out problems with the infrastructure and enforcement. For instance, imposing speed limiters before there were adequate road signs or police personnel to do so garnered criticism (Vanguard, 2017), which may have slowed down the adoption of the policy. These real-world restrictions match the model's slow changes in death patterns, which are different from the dramatic drops that happen after each policy term (2017–2024). Policy synergies and sequencing are significant. Elvik (2016) showed that combining legislation over time can have both synergistic and lag effects. The SMP model naturally allows for these kinds of interactions by adding up the lengths of states and guessing how long it will take for policies to be fully adopted. The fact that none of the lower-ranking distributions, such Weibull, gamma, or lognormal, scored better than the exponential could imply that the marginal effect of each strategy stays approximately the same over time. In short, the SMP framework is a precise and adaptable way to look at how policies change the number of collision deaths over time. It especially includes irregular timing in policy rollouts, varied hold periods, and state-dependent fatality consequences, which are not present in cross-sectional or pre/post designs (Uzondu et al., 2022; Olumide & Owoaje, 2016). This study will help policymakers to think about the long-term repercussions of their decisions and when they should make them as Nigeria pushes toward digital enforcement (NACRIS) and more universal driver profiling.

Conclusion

This study employed a semi-Markov modelling framework with exponential sojourn periods to analyze state transitions influenced by the enactment of road safety legislation in Nigeria. The findings indicated that significant improvements, like the 2003 seatbelt law, the 2017 speed limiter rule, and the 2024 initiation of NACRIS, substantially influenced the estimated duration required for interstate transitions, particularly reducing the time necessary to achieve safer outcomes. By considering the random timing of transitions and laying the groundwork for anticipating the consequences of upcoming interventions, the model made things clearer and more useful. The study underscores the importance of amalgamating statistical modelling with policy timescales to evaluate public safety initiatives and promote evidence-based decision-making.

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