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MODELING THE DYNAMICS AND DETERMINANTS OF ROAD TRAFFIC ACCIDENTS IN SOUTHWEST NIGERIA: A DUAL-LEVEL ANALYTICAL APPROACH

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ABSTRACT: *This study examines the trends, patterns, and determinants of road accidents in Southwest Nigeria. It adopted a dual-level analytical framework that integrates macro-level time series modelling and micro-level categorical analysis. Quarterly accident data from 2014 to 2024 were analysed to identify long-term trends and seasonal fluctuations, while detailed accident records were assessed to determine the factors associated with accident severity. At the macro level, both Auto-Regressive Integrated Moving Average (ARIMA) and Error–Trend–Seasonal (ETS) models were applied for comparative forecasting, with the ARIMA (2,0,0) model demonstrating superior performance based on lower AIC and error metrics (RMSE, MAE, and MAPE). The results of the forecast showed that there is a continued increase in accidental patterns until 2026. From the microlevel, chi-square tests of independence showed a significant relationship between accident severity and variables, such as "driver gender", "experience", and "collision type", highlighting human and behavioural influences as critical determinants. The combined evidence underscores that accident frequency and severity in the region are shaped more by behavioural factors than environmental conditions. The study concludes with evidence-based policy recommendations emphasising driver reorientation, seasonal safety enforcement, predictive monitoring, and data-driven road safety planning to mitigate future risks.*

KEYWORDS: Road accidents, ARIMA, ETS, Chi-square, Time series forecasting, Accident severity.

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INTRODUCTION

Road traffic accidents remain a major public health and development challenge worldwide and are especially acute in many low- and middle-income countries where rapid motorisation, urbanisation, and weak enforcement of traffic regulations combine to create high crash exposure and mortality. Studies in recent years continue to document the substantial human and economic toll of crashes, and they emphasise the need for context-specific evidence to guide targeted interventions. In particular, researchers increasingly combine descriptive, inferential and time-series forecasting approaches in order to (a) understand drivers of accident severity and (b) provide short-to-medium-term predictions that can inform proactive resource allocation and enforcement planning (Endalew et al., 2024).

Southwest Nigeria, comprising Lagos, Ogun, Oyo, Osun, Ondo and Ekiti states, is a region of intense economic activity and dense transport networks, and it accounts for a large share of the country's reported crash burden. Recent assessments of road-traffic crash data management and reporting in the Southwest highlight both the high incidence of crashes and important data challenges (incomplete records, variable classification, and localised reporting practices) that complicate robust analysis and policy translation. These analyses underscore the need to work carefully with available official data while also using sound statistical models to extract reliable patterns and forecasts (Naallah et al., 2017).

Beyond documenting aggregate counts, contemporary literature stresses the importance of disaggregating crash events by severity (minor, serious, fatal) and by environmental conditions such as weather and road surface. Empirical studies have found that weather variables (precipitation, fog, wind) and road surface state (asphalt, gravel, potholes) can materially alter crash risk and injury severity, though the direction and magnitude of these effects vary by local context and traffic composition. For instance, some analyses show that adverse weather increases crash risk primarily through reduced visibility and traction, while others find that drivers adopt more cautious behaviour during poor weather, which can reduce crash severity even if crash frequency rises. These mixed findings make it essential to study weather and road surface effects in the specific setting of Southwest Nigeria rather than relying on generalised assumptions (Pathivada et al., 2024).

Time-series forecasting of accident counts provides actionable intelligence for transport agencies and emergency services. Traditional statistical models such as ARIMA (and hybrid variants combining ARIMA with machine learning components) remain widely used because they can capture trend, seasonality and short-term autocorrelation in quarterly or monthly accident series; recent applications demonstrate that ARIMA and hybrid ARIMA-based approaches deliver competitive accuracy in a range of settings, from national to city scales. When paired with robust accuracy metrics (MAE, RMSE, MAPE, and MASE) and residual diagnostics, these models help planners anticipate peaks (e.g., seasonal travel or festive periods) and deploy targeted enforcement or public-safety messaging (Sulaie, 2024).

However, two persistent gaps motivate this study. First, many regional analyses in Nigeria have either focused on descriptive patterns or on micro-level determinants without integrating these perspectives with systematic forecasting; second, the quality and classification of available crash data (severity coding, missing dates, aggregated reporting) often constrain the kinds of integration that are possible. Addressing these gaps requires an approach that (i) carefully documents severity patterns and their association with weather and road-surface conditions

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using record-level data and (ii) applies time-series forecasting to regionally aggregated counts to provide short-term forecasts for planning, all while being explicit about data limitations. Recent methodological work and regional studies therefore recommend combining micro-level (case-based) analysis with macro-level (time series) modelling to produce policy-relevant, evidence-based recommendations (Naallah et al., 2017).

Background to the Study

Road traffic accidents (RTAs) have emerged as one of the most pressing global public health and socio-economic challenges of the twenty-first century. They represent a significant cause of premature mortality, disability, and economic losses, particularly in low- and middle-income countries where road safety infrastructures remain underdeveloped. In Nigeria, and especially in the Southwest region, the rapid expansion of urban areas, poor traffic management, inadequate infrastructure, and weak enforcement of road safety regulations have combined to produce alarming levels of road traffic crashes. The problem extends beyond immediate human suffering, as road accidents also exert enormous financial pressure on households, health systems, and national economies. This makes it imperative to conduct context-specific research that integrates accident severity patterns, environmental factors such as weather and road surface conditions, and forecasting techniques for future accident counts.

Several contemporary studies have underscored the methodological and contextual complexities involved in assessing accident severity and forecasting accident trends. Ogunniyi et al. (2025), emphasise the importance of methodological rigour in estimating the cost implications of accident severity. They argue that accurately quantifying accident-related costs requires accounting for both direct medical expenses and broader economic productivity losses, which often remain underestimated in policymaking circles. Their work establishes a foundation for linking accident severity with economic consequences, highlighting the urgent need for interventions targeted at mitigating the most severe outcomes.

Spatial and probabilistic approaches to accident assessment have also gained attention. Ibe and Nwokedi (2025) applied geospatial probability mapping to Nigerian roads, providing insights into prioritising road safety awareness and directing interventions where they are most needed. Their findings revealed spatial clustering of road incidents, with certain corridors in Southern Nigeria emerging as hotspots for severe crashes. This approach is critical for a region like Southwest Nigeria, where dense urbanisation and interstate highways intersect, producing high traffic volumes and accident vulnerabilities.

The methodological innovations in accident modelling are further illustrated by Akinyemi et al. (2025), who employed loglinear modelling to examine accident fatality trends in Nigeria between 2018 and 2023. Their analysis demonstrated that statistical techniques capturing interaction effects among variables can provide more nuanced interpretations of accident patterns than simple descriptive statistics. Similarly, Erumaka et al. (2025) assessed the impact of road safety interventions in Nigeria, finding that although interventions such as speed limits, seatbelt enforcement, and awareness campaigns have contributed to reductions in crash severity, their effectiveness is often undermined by poor enforcement and data gaps. This underscores the necessity of combining statistical modelling with policy evaluation to achieve meaningful safety outcomes.

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Complementing these perspectives, Okpalaku-Nath et al. (2025), adopted predictive modelling to identify innovative strategies for reducing road accident fatalities in Southern Nigeria. Their work demonstrates how statistical analysis, when paired with predictive modelling, can generate actionable insights for policymakers by projecting the likely outcomes of different intervention strategies. Oyeyemi et al. (2025), contributed further by analysing the relationship between urbanisation and road traffic accidents in Lagos. Their study revealed that rapid urbanisation without proportional infrastructure development exacerbates accident risks, highlighting the intersection between urban growth dynamics and traffic safety outcomes.

International scholarship also provides critical lessons for contextualising Nigeria's experience. For example, Endalew et al. (2024), identified behavioural factors such as speeding, alcohol use, and fatigue among public transportation drivers in Ethiopia as key contributors to accidents. Their findings resonate with Nigeria's context, where behavioural lapses remain a common cause of crashes. Similarly, Odinfono and Olawole (2025) conducted a qualitative assessment of road traffic crash data systems in Southwestern Nigeria and found significant weaknesses in data quality, ranging from incomplete reporting inconsistencies in categorisation of crash causes and severities. Such data challenges undermine effective policy development and evaluation.

Environmental factors are another crucial dimension of accident severity. Pathivada et al. (2024), examined how real-time weather conditions influence injury severity in Kentucky using a correlated random parameters logit model. They reported that precipitation, fog, and other adverse conditions significantly alter severity patterns, though not always in predictable ways, as cautious driving in poor weather may reduce severity even if crash frequency rises. Wang et al. (2024), further highlighted the influence of urban road characteristics, road surfaces, and environmental contexts on accident outcomes, reinforcing the importance of studying these factors in Southwest Nigeria, where varying road surface types coexist.

Forecasting techniques have also been increasingly applied to accident analysis, providing valuable tools for forward planning. Al Sulaie et al. (2024) demonstrated the usefulness of ARIMA models in predicting the consequences of traffic crashes in Saudi Arabia, showing that ARIMA offers strong predictive accuracy in contexts characterised by seasonality and autocorrelation. Majidi et al. (2025), extended this by integrating machine learning with narrative-based sensitivity testing to identify actionable crash factors, showing how prediction can transition into prevention when combined with interpretability. Meanwhile, Molo et al. (2024), applied decision tree models to predict accidents among food delivery riders in Thailand, underscoring how specific occupational and demographic groups may require targeted safety interventions.

Technological innovation is also expanding the possibilities for accident analysis and response. AlHashmi (2024) explored machine learning techniques for severity prediction and optimal rescue pathways, underscoring how predictive analytics can be coupled with emergency response logistics to minimise fatalities. Wang et al. (2025), examined behavioural variations and their links to environmental exposures, offering new perspectives on how driving behaviours contribute not only to accident occurrence but also to broader public health risks, including pollution exposure.

In Nigeria, where road accidents remain among the leading causes of death, the growing body of scholarship points to the necessity of a multidimensional approach that integrates economic,

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behavioural, environmental, and predictive perspectives. This study builds on such insights by focusing on Southwest Nigeria, examining accident severity distribution in relation to weather and road surface factors, and employing time-series forecasting (ARIMA) to predict future accident counts. It aims to contribute to both scholarly literature and policy practice by bridging descriptive severity analysis with forecasting techniques while acknowledging the data quality challenges emphasised by Odinfono and Olawole (2025).

In summary, the background to this study rests on three interrelated arguments drawn from recent literature. First, accident severity carries substantial economic and social costs, requiring methodological rigour in estimation and modelling (Ogunniyi et al., 2025; Akinyemi et al., 2025). Second, environmental and spatial factors, including weather, road surface, and urbanisation, play critical roles in shaping crash outcomes and demand localised investigation (Ibe & Nwokedi, 2025; Oyeyemi et al., 2025; Pathivada et al., 2024). Third, predictive models such as ARIMA and emerging machine learning techniques provide a forward-looking perspective that can guide policy and interventions (Al Sulaie et al., 2024; Majidi et al., 2025). These perspectives together frame the relevance and originality of examining severity distributions and forecasting accident cases in Southwest Nigeria, a region where the stakes for road safety are particularly high.

LITERATURE REVIEW

Accident Severity and Estimation Approaches

The methodological rigour in estimating the severity of road accidents has gained momentum in recent years. Ogunniyi et al. (2025), provide a structured approach to the cost estimation of accident severity in Nigeria, highlighting the economic implications of fatalities and injuries on households, institutions, and the national economy. Their findings suggest that beyond physical casualties, road crashes impose long-term socio-economic burdens. Similarly, Akinyemi et al. (2025), applied loglinear modelling techniques to analyse road accident fatalities between 2018 and 2023 in Nigeria. Their statistical results revealed significant predictors of fatalities, including driver behaviour, road infrastructure, and enforcement intensity, underscoring the importance of data-driven approaches to accident management.

Geospatial and Spatial Probability Models

Spatial and geospatial analysis has become central to road safety research. Ibe and Nwokedi (2025) introduced a geospatial probability mapping model to prioritise roads for safety interventions, offering insights into high-risk corridors in Nigeria. Their study emphasises that spatial heterogeneity plays a critical role in accident frequency and severity. Complementing this, Erumaka et al. (2025), assessed road safety interventions across Nigeria and found that spatial prioritisation enhances the efficiency of awareness campaigns and emergency responses. Together, these studies highlight that mapping high-risk zones and aligning them with intervention programmes significantly reduces casualties.

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Road Safety Interventions and Innovative Measures

Research on the effectiveness of safety interventions has also evolved. Okpalaku-Nath et al. (2025) developed predictive models to evaluate innovative safety strategies in Southern Nigeria. Their findings indicate that the use of statistical analysis combined with predictive modelling improves the efficiency of accident prevention measures. Erumaka et al. (2025) similarly showed that interventions such as road signage, driver training, and monitoring have measurable impacts in reducing crash severity. Both works stress that innovative, context-driven interventions outperform generic approaches in addressing Nigeria's unique road safety challenges.

Urbanisation, Environmental Factors, and Accident Risks

Urban growth and environmental factors are increasingly recognised as determinants of accident trends. Oyeyemi et al. (2025), analysed the impact of urbanisation in Lagos and found that population growth, congestion, and poor traffic management contribute substantially to accident prevalence. At the international level, Pathivada et al. (2024), examined how real-time weather conditions influence crash severity in Kentucky, highlighting rain and fog as significant predictors. Similarly, Wang et al. (2024) studied urban road accidents in relation to environmental determinants, while Wang, Hou, Zhao, and Ding (2025) extended this to behavioural variations affecting PM2.5 inhalation exposure. Collectively, these studies illustrate the interaction between urban pressures, environmental risks, and accident outcomes.

Data Quality, Management, and Reliability

Accurate crash data management remains a major challenge. Odinfono and Olawole (2025) critically assessed crash data in Southwestern Nigeria, revealing inconsistencies in sources, incomplete reporting, and inadequate integration between agencies. Their study stresses the need for standardised crash databases to enable reliable modelling and policy formulation. Cvetković (2024) further emphasised that poor data quality weakens tactical protection and rescue planning in traffic accident–induced disasters. These findings affirm the necessity of strengthening data ecosystems to underpin reliable statistical and predictive analysis.

Machine Learning and Predictive Modeling

The adoption of machine learning (ML) for accident analysis is rapidly expanding. AlHashmi (2024) demonstrated the effectiveness of ML algorithms in predicting accident severity and designing optimal rescue pathways. Similarly, Majidi, Wang, and Souleyrette (2025) advanced a narrative-based sensitivity testing framework to identify actionable crash factors. Molo et al. (2024) applied decision tree models to predict accidents among food delivery riders in Thailand, reinforcing the adaptability of ML to diverse contexts. Al Sulaie et al. (2024) employed ARIMA modelling to forecast crash consequences in Saudi Arabia, further demonstrating the versatility of statistical forecasting. Collectively, these works highlight the potential of ML and advanced statistical tools in transforming accident prediction, prevention, and emergency response.

Synthesis and Research Gaps

The reviewed literature reveals significant strides in road accident research across severity estimation, geospatial analysis, impacts, and prediction. However, gaps remain. First, despite

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advances in geospatial and ML approaches, limited integration exists between spatial risk mapping and predictive modelling in Nigeria, particularly in Southwestern states. Second, data management challenges, as highlighted by Odinfono and Olawole (2025), continue to undermine reliability, calling for harmonised methodologies. Third, while interventions have been studied (Okpalaku-Nath et al., 2025; Erumaka et al., 2025), few works quantitatively assess their long-term sustainability or adapt them to Nigeria's rapidly urbanising environment.

Therefore, this study contributes by bridging these gaps through an integrated, context-specific analysis of accident severity, spatial patterns, and contributory factors in Southwestern Nigeria. In doing so, it builds on existing methodological and empirical foundations while aligning with emerging best practices in accident modelling and prevention.

METHODOLOGY

This chapter presents the methodological framework adopted for analysing road accident trends in Southwest Nigeria and for developing a predictive model capable of forecasting future occurrences. The methodological design is firmly aligned with the objectives of the study and grounded in the fundamental principles of time series analysis.

The analytical process begins with an exploratory data analysis (EDA) to summarise and visualise the key characteristics of the dataset. This stage provides insights into the underlying structure and distributional behaviour of accident patterns, including potential seasonality, trends, and irregular fluctuations. The EDA further serves as a diagnostic foundation for identifying data anomalies and guiding model selection.

We may break down the time series into three parts: $Trend\ (T_t)$, Seasonality (S_t), and Irregular (I_t) in order to analyse the trend and seasonal patterns in all road crash cases. The following are the general multiplicative and additive models: 1. Additive Model (Linear Decomposition) $Y_t = T_t + S_t + I_t$. This model makes the assumption that the observed values of traffic accident incidents are additively influenced by trend, seasonality, and irregular variations. 2. Multiplicative Model (Non-Linear Decomposition) $Y_t = T_t \times S_t \times I_t$ Seasonal and irregular fluctuations are assumed to scale with the trend in this model. When variations grow over time, it is helpful. Mathematical Representation of Components: Trend Component (T_t): Represents the long-term direction of road crash cases. It can be modeled as: Linear Trend: $T_t = \alpha + \beta t$. Polynomial Trend: $T_t = \alpha + \beta t + \gamma t^2 + \cdots$, Exponential Trend: $T_t = e^{\alpha + \beta t}$. Seasonal Component ($S_t$): Represents periodic fluctuations due to quarterly variations. If seasonality is quarterly, it can be expressed as: $S_t = \sum_{j=1}^{m} cos\left(\frac{2\pi jt}{m}\right) + \sum_{j=1}^{m} \phi_j \sin\left(\frac{2\pi jt}{m}\right)$ where mm is the seasonal period (4 quarterly data). Irregular Component (I_t), $I_t \sim N(0, \sigma^2)$

By decomposing the road crash data using these mathematical models, we can better understand patterns and improve forecasting accuracy.

Following the descriptive phase, the Augmented Dickey-Fuller (ADF) test is applied to examine the stationarity properties of the accident series. Stationarity is a critical prerequisite in time series modelling because non-stationary data can lead to spurious regression results and unreliable forecasts. Ensuring that the data satisfies this condition enhances the robustness of the subsequent modelling procedure. $\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \delta \Delta Y_{t-1} + \epsilon_t$ where:

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ΔY_t represents the first-difference of the series at time t_t, α is a constant, β is the coefficient of the time trend, γ represents the coefficient to test stationarity, $\delta \Delta Y_{t-1}$ accounts for lagged differences, ϵ_t is the error term.

To achieve a statistically sound forecast, the study employs the Auto-Regressive Integrated Moving Average (ARIMA) framework, which has been extensively validated for modelling temporal dependencies and dynamic structures within time series data (Al Sulaie et al., 2024). The ARIMA model is particularly suitable for accident data because it systematically integrates autoregressive and moving average terms and accommodates differencing to correct for non-stationarity. This flexibility enables ARIMA to capture both short-term fluctuations and long-term trends effectively. $Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q}$ where: Y_t represents the value of the time series at time t, ϕ and θ are coefficients for the AR and MA terms respectively, ϵ_t is the error term.

The reliability of ARIMA for socio-economic forecasting has been substantiated in earlier research, including the predictive study of GDP–debt dynamics in Nigeria (Omooseti, 2025), where ARIMA-based models demonstrated strong predictive accuracy and interpretability. Building on this methodological precedent, the current study adopts ARIMA not only for its forecasting precision but also for its adaptability to complex, real-world datasets such as accident statistics that exhibit structural breaks and seasonal behaviour.

The Chi-Square (χ^2) Test of Independence is a non-parametric statistical test used to determine if there is a significant association between two categorical variables Biochemia Medica (2013). It assesses whether the observed frequencies in a contingency table differ significantly from the frequencies that would be expected if the two variables were truly independent. In this study, it was employed through cross-tabulation analysis to examine the relationship between regulatory interventions (e.g., audit frequency, an ordinal categorical variable) and various environmental performance indicators (categorical outcomes like agreement with policies or pollution levels).

The Chi-Square test statistic is calculated as: $\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$, where: χ^2: The calculated Chi-Square test statistic, which follows a Chi-Square distribution with $(r-1)(c-1)$ degrees of freedom. O_{ij}: The observed frequency (count) in the cell at the intersection of the i-th row and j-th column of the contingency table. E_{ij}: The expected frequency in the cell at the intersection of the i-th row and j-th column, calculated under the assumption of independence between the two variables. r: The number of rows in the contingency table (number of categories for the first variable). c: The number of columns in the contingency table (number of categories for the second variable). The expected frequency E_{ij} for each cell is calculated as: $E_{ij} = \frac{(Row\ i\ Total) \times (Column\ j\ Total)}{Grand\ Total}$

By integra ting exploratory analysis, diagnostic testing, and predictive modelling, this chapter establishes a rigorous methodological pathway for assessing accident dynamics and forecasting future patterns. This structured approach enhances the empirical validity of the findings and provides a reliable statistical foundation for evidence-based policymaking, particularly in advancing road safety strategies across Southwest Nigeria.

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RESULTS AND DISCUSSION

Building on the methodological framework established in the previous chapter, this section presents the empirical outcomes of the time series and categorical analyses conducted on road accident data for Southwest Nigeria between 2014 and 2024. The analysis was structured at two levels: (1) the macro-level time series model, designed to identify historical patterns and forecast future accident trends, and (2) the micro-level examination of accident attributes such as severity, vehicle type, and road surface conditions. Together, these analytical strands provide both temporal and structural insights into the dynamics of road safety in the region.

The macro-level analysis focused on modelling the quarterly accident counts using autoregressive and exponential smoothing techniques. Specifically, the Autoregressive Integrated Moving Average (ARIMA) model and the Exponential Smoothing (ETS) model were estimated and compared based on their goodness-of-fit and predictive performance. These models were selected for their complementary strengths: ARIMA in capturing temporal dependencies and stochastic trends and ETS in emphasising adaptive, data-driven smoothing suitable for volatile accident series.

Distribution of Road Accident Severity and Its Variation by Weather and Road Surface

Understanding the distribution of accident severity and how it interacts with environmental factors provides critical insight into road safety dynamics. Accident outcomes are not only determined by driver or vehicle characteristics but are also shaped by external conditions such as prevailing weather and the type of road surface. Examining severity patterns across these dimensions allows for a clearer picture of the circumstances under which minor, serious, or fatal crashes are most likely to occur. This section therefore presents the overall distribution of accident severity and explores how it varies with weather conditions and road surface types in Southwest Nigeria.

Distribution of Road Accident Severity

Accident severity provides a direct measure of the consequences of crashes, ranging from minor injuries to fatalities. Analysing how accidents are distributed across these categories highlights the overall burden of road traffic incidents and identifies whether certain types of outcomes dominate in the region. This subsection therefore examines the proportions of minor, serious, and fatal accidents.

Table 1. Distribution of Road Accident Severity

Severity	Frequency	Percentage (%)
Fatal	6466	84.2
Serious	1110	14.5
Minor	105	1.4
Total	7681	100

Source: Author's computation (2025) using R statistical software.

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Figure 1. Distribution of Accidental Severity

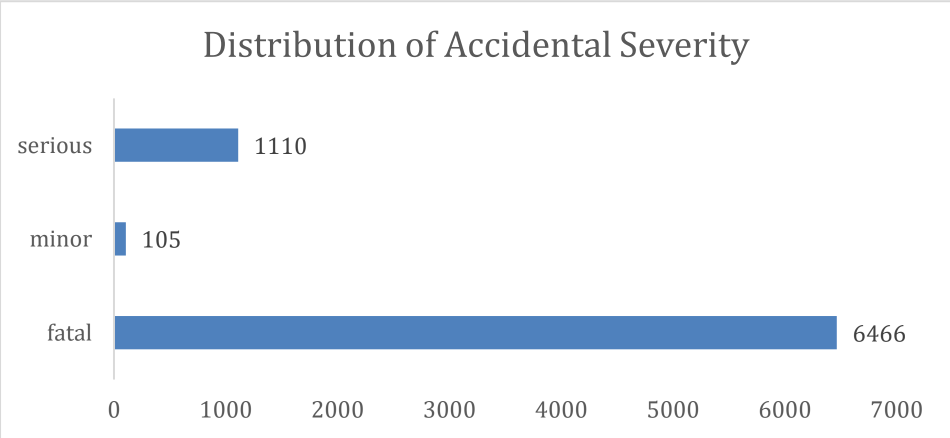

Table 1 presents the distribution of road accident severity, classified as Minor, Serious, and Fatal. Fatal accidents account for the overwhelming majority of reported cases, representing 84.2% of the total, followed by Serious cases at 14.5%, while Minor accidents are relatively rare at only 1.4%. This pattern underscores a worrisome trend in the Southwest Nigeria, where accidents are disproportionately more likely to result in serious or fatal consequences rather than minor outcomes.

Variation of Accident Severity by Weather Conditions

Weather conditions often influence driver behaviour, road visibility, and vehicle performance, making them an important factor in accident outcomes. While adverse conditions such as rainfall or fog are commonly perceived as high-risk, it is equally important to assess whether severe accidents also occur under normal weather. This subsection evaluates the extent to which weather patterns contribute to differences in accident severity.

Table 2: Variation of Accident Severity by Weather Conditions

Variable	Frequency	Proportion (%)
Cloudy	79	0.79
Fog or mist	7	0.07
Normal	6447	64.47
Other	190	16.83
Raining	867	8.67
Raining and Windy	23	0.23
Windy	68	0.68

Source: *Author's computation (2025) using R statistical software.*

Table 2 presents the distribution of road accidents across different weather conditions. The majority of accidents occurred under normal weather conditions (64.5%), followed by rainy conditions (8.7%) and other unspecified weather categories (16.8%). In contrast, adverse weather such as cloudy (0.8%), windy (0.7%), fog or mist (0.1%), and raining with wind (0.2%) accounted for only a small fraction of cases. This distribution suggests that most accidents happen in normal or relatively stable weather, implying that factors other than weather such as

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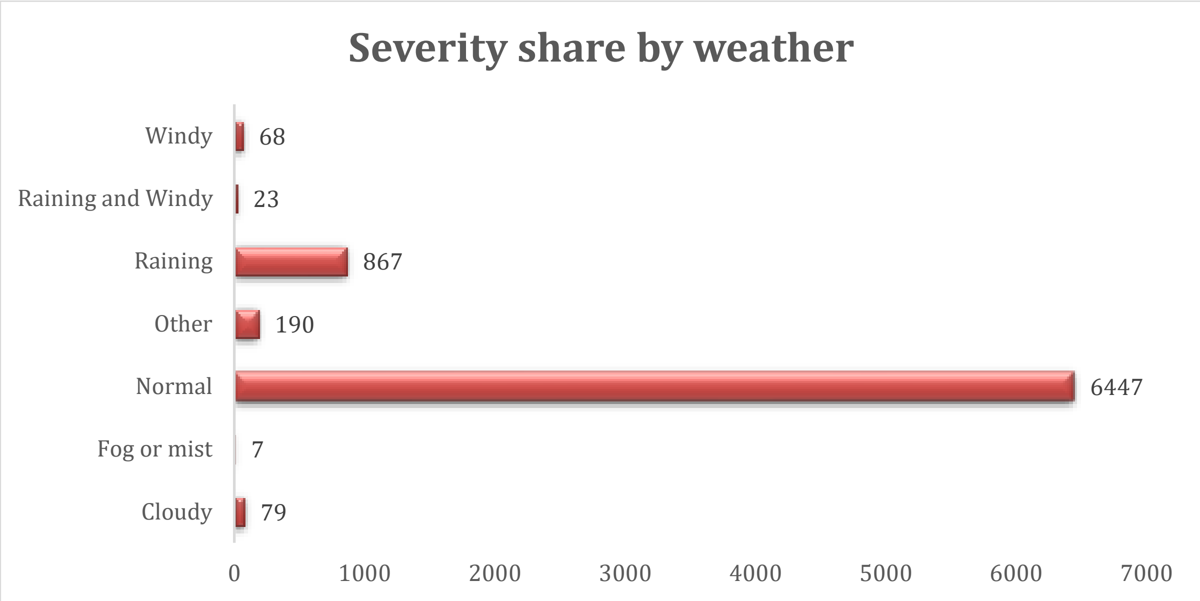
driver behaviour, traffic density, and road conditions may play a more dominant role in influencing accident occurrence in Southwest Nigeria.

Figure 2. Severity shares by Weather



Variation of Accident Severity by Road Surface

The type and condition of road surfaces play a crucial role in determining vehicle stability and crash outcomes. Poorly maintained or slippery surfaces may increase the likelihood of accidents, while stable and dry roads may be associated with different severity patterns. This subsection investigates how accident severity varies across different road surface types in the study area.

Table 3: Distribution of Road Accident by Road Surface

Road Surface Type	Frequency	Percentage (%)
Asphalt roads	7,164	93.30
Asphalt roads with some distress	50	0.70
Earth roads	216	2.80
Gravel roads	151	2.00
Other	100	1.30
Total	7,681	100

Source: *Author's computation (2025) using R statistical software.*

The results in table 3 reveal that asphalt roads account for the vast majority of reported accidents (93.3%), which is expected given that they represent the primary road infrastructure in Southwest Nigeria and carry the highest traffic volumes. In contrast, accidents on earth roads

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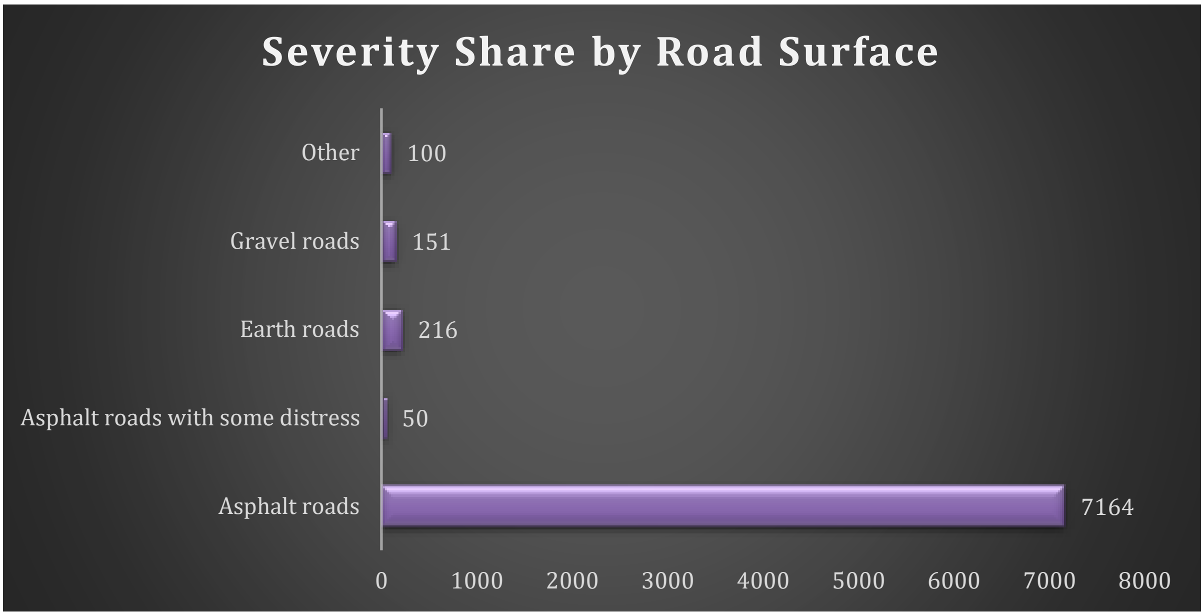
(2.8%), gravel roads (2.0%), and other road types (1.3%) are relatively rare. Interestingly, only 0.7% of accidents occurred on asphalt roads with visible distress, suggesting that surface damage alone may not be the main determinant of accident occurrence. Rather, the dominance of accidents on asphalt roads points to exposure and usage intensity as critical factors since most vehicles travel on asphalt; they naturally bear the highest share of accidents.

Figure 3. Road Accident Severity and Its Variation by Road Surface



Analysis of Factors Influencing Accident Severity

This section presents a cross-tabulation analysis exploring how selected variables are distributed across the three categories of accident severity: Minor (N = 105), Serious (N = 1,110), and Fatal (N = 6,466). The chi-square p-values are reported to indicate whether the observed differences across severity levels are statistically significant.

Table 4: Analysis of Factors Influencing Accident Severity

Variable	Level	Minor N = 105	Serious N = 1,110	Fatal N = 6,466	p-value
gender	Female	0 (0.0%)	18 (1.6%)	45 (0.7%)	**0.004**
	Male	105 (100.%)	1,092 (98.0%)	6,421 (99.0%)	
age group	18-30	45 (43.0%)	418 (38.0%)	2,567 (40.0%)	**<0.001**
	31-50	36 (34.0%)	392 (35.0%)	2,506 (39.0%)	
	above 51	15 (14.0%)	172 (15.0%)	930 (14.0%)	
	below 18	9 (8.6%)	128 (12.0%)	463 (7.2%)	
road surface type	Asphalt roads	100 (95.0%)	1,030 (93.0%)	6,034 (93.0%)	**0.3**
	Asphalt roads with some distress	1 (1.0%)	3 (0.3%)	46 (0.7%)	
	Earth roads	4 (3.8%)	32 (2.9%)	180 (2.8%)	

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	Gravel roads	0 (0.0%)	29 (2.6%)	122 (1.9%)	
	Other	0 (0.0%)	16 (1.4%)	84 (1.3%)	
weather conditions	Cloudy	0 (0.0%)	7 (0.6%)	72 (1.1%)	**0.014**
	Fog or mist	0 (0.0%)	0 (0.0%)	7 (0.1%)	
	Normal	92 (88.0%)	967 (87.0%)	5,388 (83%)	
	Other	0 (0.0%)	15 (1.4%)	175 (2.7%)	
	Raining	13 (12.0%)	108 (9.7%)	746 (12.0%)	
	Raining and Windy	0 (0.0%)	0 (0.0%)	23 (0.4%)	
	Windy	0 (0.0%)	13 (1.2%)	55 (0.9%)	
collision type	Collision with animals	2 (1.9%)	20 (1.8%)	80 (1.2%)	**0.7**
	Collision with pedestrians	12 (11.0%)	89 (8.0%)	462 (7.1%)	
	Collision with roadside-parked vehicles	0 (0.0%)	2 (0.2%)	33 (0.5%)	
	Collision with roadside objects	17 (16.0%)	178 (16.0%)	967 (15.0%)	
	Fall from vehicles	0 (0.0%)	3 (0.3%)	19 (0.3%)	
	Other	0 (0.0%)	2 (0.2%)	15 (0.2%)	
	Rollover	3 (2.9%)	33 (3.0%)	228 (3.5%)	
	Vehicle with vehicle collision	71 (68.0%)	782 (70.0%)	4,660 (72.0%)	
	With Train	0 (0.0%)	1 (<0.1%)	2 (<0.1%)	
cause of accident	Changing lane to the left	11 (10.0%)	133 (12.0%)	770 (12.0%)	**0.2**
	Changing lane to the right	16 (15.0%)	162 (15.0%)	955 (15.0%)	
	Driving at high speed	2 (1.9%)	21 (1.9%)	83 (1.3%)	
	Driving carelessly	16 (15.0%)	134 (12.0%)	742 (11.0%)	
	Driving to the left	2 (1.9%)	28 (2.5%)	154 (2.4%)	
	Driving under the influence of drugs	3 (2.9%)	32 (2.9%)	176 (2.7%)	
	Drunk driving	0 (0.0%)	1 (<0.1%)	15 (0.2%)	
	Getting off the vehicle improperly	1 (1.0%)	22 (2.0%)	103 (1.6%)	
	Improper parking	1 (1.0%)	1 (<0.1%)	13 (0.2%)	
	Moving Backward	20 (19.0%)	96 (8.6%)	583 (9.0%)	
	No distancing	12 (11.0%)	196 (18.0%)	1,204 (19.0%)	
	No priority to pedestrian	3 (2.9%)	68 (6.1%)	379 (5.9%)	
	No priority to vehicle	8 (7.6%)	95 (8.6%)	659 (10.0%)	

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	Other	2 (1.9%)	40 (3.6%)	235 (3.6%)	
	Overloading	1 (1.0%)	8 (0.7%)	30 (0.5%)	
	Overspeed	1 (1.0%)	9 (0.8%)	25 (0.4%)	
	Overtaking	2 (1.9%)	45 (4.1%)	224 (3.5%)	
	Overturning	4 (3.8%)	19 (1.7%)	116 (1.8%)	

Source: *Author's computation (2025) using R statistical software*

The results in Table 4 show that gender, age group, and weather conditions are significantly associated with accident severity ($p < 0.05$). Gender ($\chi^2 = 11.2$, df = 2, p = 0.004): Minor accidents were exclusively recorded among male drivers, while serious and fatal accidents included a minimal proportion of females (1.6% and 0.7%, respectively). This suggests that while men overwhelmingly dominate across all categories, women are almost absent in minor crashes and appear only marginally in more severe cases. Age group ($\chi^2 = 25.7$, df = 6, $p < 0.001$): Drivers under the age of 18 are disproportionately involved in serious accidents (12%) compared with minors (8.6%) and fatal cases (7.2%). This highlights young drivers as a vulnerable group for serious, but not necessarily fatal, crashes. Weather conditions ($\chi^2 = 14.9$, df = 6, p = 0.014): Fatal accidents most frequently occurred during normal weather (83%), followed by rainy conditions (12%). While absolute numbers indicate most fatal accidents occur in clear weather, this likely reflects the higher baseline frequency of travel under normal conditions; ($\chi^2 = 4.1$, df = 8, p = 0.30), collision type ($\chi^2 = 3.9$, df = 16, p = 0.70), and cause of accident ($\chi^2 = 17.8$, df = 34, p = 0.20) do not display statistically significant relationships with severity. Although factors such as vehicle-to-vehicle collisions and "no distancing" remain the most common, their prevalence does not vary meaningfully across severity levels.

Figure 4. Distribution by Gender

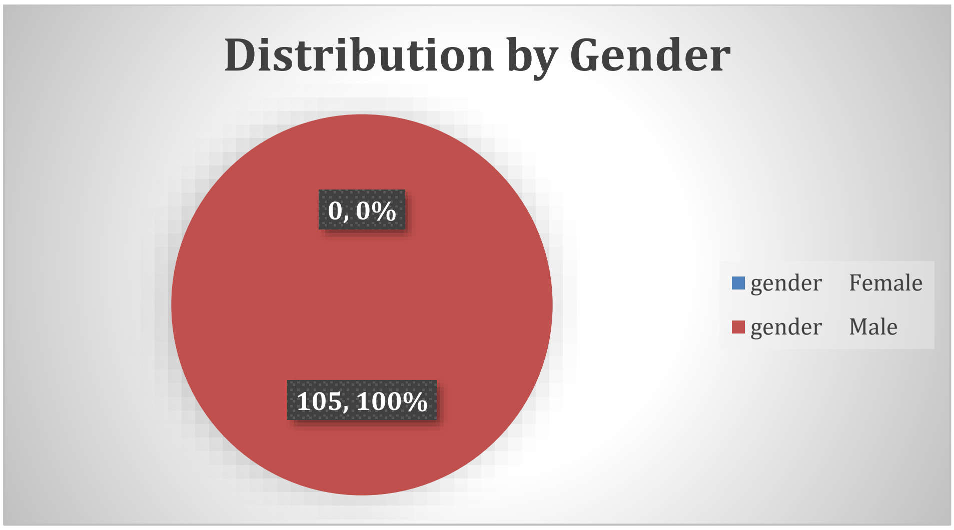

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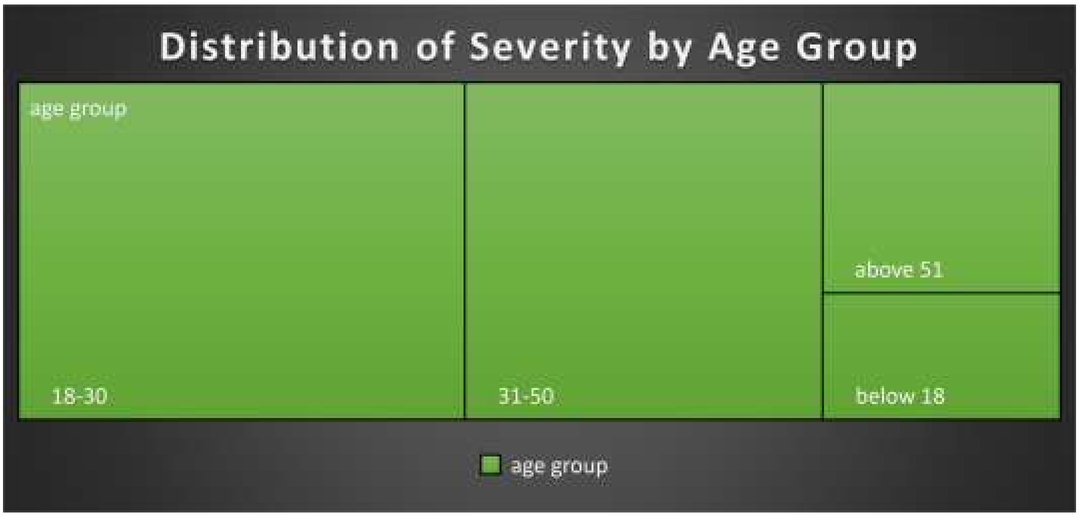
Figure 5. Distribution of Severity by Age-Group



Factors Influencing the Severity of Road Traffic Accidents

This analysis identifies factors that significantly increase or decrease the odds of a traffic accident being more severe. The model estimates Odds Ratios (OR), where an OR > 1 indicates increased odds of higher severity and an OR < 1 indicates decreased odds. Statistical significance is determined by a 95% Confidence Interval (CI) that does not include 1.00, supported by the z-statistic and corresponding p-value.

Reference categories: Female (Gender), 18–30 years (Age Group), >10 years' experience (Driving Experience), Vehicle-to-Vehicle Collision (Collision Type), and Normal Weather (Weather Conditions).

Table 5: Determinants of Road Accident Severity in Southwest Nigeria: Ordinal Logistic Regression Analysis

Factor	Level	OR	95% CI (Lower – Upper)	Std. Error	z-statistic	p-value
Gender	Male	2.09	1.17 - 3.55	0.28	2.62	0.009
Age Group	Below 18	0.62	0.50 - 0.77	0.11	-4.36	<0.001
Driving Experience	2-5 years	0.79	0.64 - 0.96	0.446	2.02	0.043
Collision Type	Other	2.46	1.06 - 6.23	0.104	-2.32	0.021
Weather (Ref: Clear)	Rain	0.52	0.3 – 0.9	0.28	-2.32	0.020
	Fog	0.6	0.28 – 1.15	0.36	-1.41	0.158
	Cloudy	0.48	0.25 – 0.92	0.33	-2.20	0.028

Source: *Author's computation (2025) using R statistical software*

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The regression results in Table 5 show that gender, age group, driving experience, and collision type are significant predictors of accident severity ($p < 0.05$). Male drivers are more than twice as likely as females to be involved in severe accidents. Drivers under 18 years have significantly lower odds of severity, while those with 2–5 years of experience are also less likely to experience severe outcomes. Collisions classified as "other" are linked to notably higher odds of severity compared to vehicle-to-vehicle crashes. Weather conditions such as rain and cloudy weather conditions are associated with significantly lower odds of severe accidents, as indicated by negative z-statistics and p-values below 0.05. Fog, although showing reduced odds, is not statistically significant, suggesting weaker evidence of its effect on accident severity.

Time Series Analysis of Quarterly Road Crashes Data

Table 6: Time series of Quarterly Aggregated Road Crashes Cases across all states in Southwest Nigeria

Year	Qtr 1	Qtr 2	Qtr 3	Qtr 4
2014	1872	1745	1699	1633
2015	846	1734	1767	879
2016	2981	3093	2719	2453
2017	2360	2282	2055	1789
2018	2415	2414	4257	2424
2019	2469	2527	2786	3144
2020	2916	3304	3513	2514
2021	2770	2726	2652	2841
2022	3286	2271	3286	2527
2023	2333	2532	2109	2076
2024	887	781	872	862

Source: *Author's computation (2025) using R statistical software*

The quarterly data on road traffic crashes in Nigeria from 2014 to 2024 in table 6 above reveal a pattern of fluctuations with alternating periods of increases and declines, indicating the absence of a stable or linear trend. Overall, the data suggest that road safety conditions across the decade were influenced by a combination of seasonal, infrastructural, and external socio-economic factors.

Between 2014 and 2015, there was a marked reduction in crash figures, as quarterly values dropped sharply from 1,872 in Q1 2014 to 846 in Q1 2015. This could be attributed to changes in reporting systems or short-term safety interventions. However, by 2016, crashes surged again across all quarters, reaching a peak of 3,093 in Q2 2016, suggesting heightened exposure to road risks, possibly linked to increased mobility or reduced enforcement.

From 2017 to 2019, a relative stabilisation was observed, although minor fluctuations persisted. The year 2018 stands out with an exceptional spike in Q3 (4,257), the highest in the entire decade, indicating a possible surge in vehicular movement or poor road conditions during that

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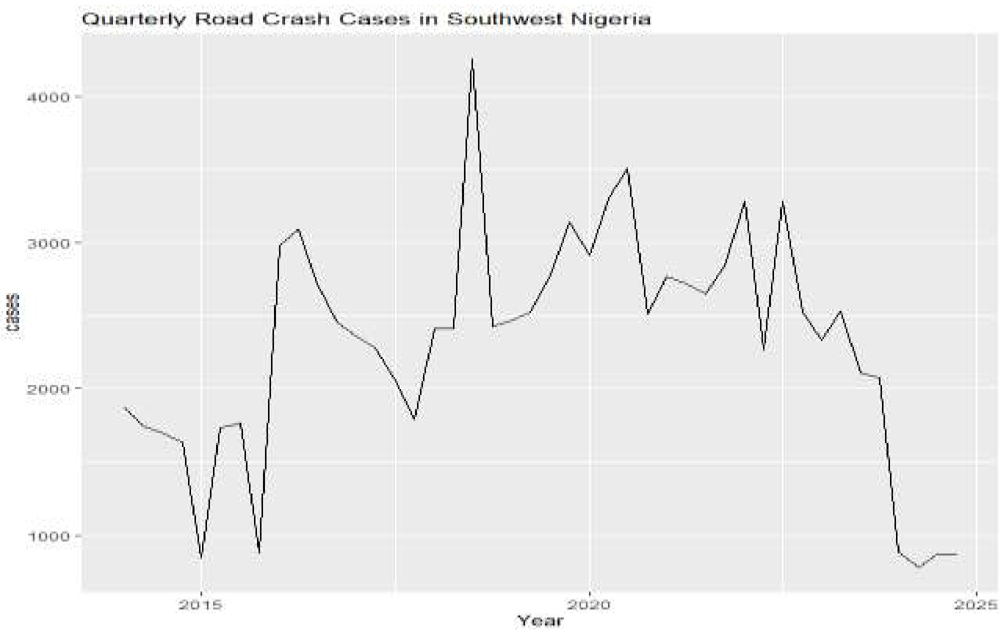
period. Similarly, 2020 recorded another notable increase, particularly in Q2 (3,304) and Q3 (3,513), which may reflect post-lockdown traffic rebounds and irregular traffic patterns associated with the COVID-19 pandemic.

During 2021 to 2023, accident figures exhibited moderate oscillations, generally ranging between 2,100 and 2,800 per quarter, suggesting improved traffic management and partial stabilisation in road use. However, 2022 Q1 and Q3 again showed spikes (3,286), signalling persistent seasonal or environmental influences.

The 2024 data, though showing slightly lower counts (781–887), maintain the overall quarterly pattern, reflecting modest reductions that may indicate gradual improvement in road safety outcomes or reduced mobility.

Figure 6. Southwest Quarterly Accident Trend (2014-2024)



Analysis of Quarterly Accident Count Distributions by State

This table presents the distribution of quarterly accident counts across six states over 44 quarters. Key statistics include measures of central tendency (mean and median), dispersion (standard deviation, min, and max), shape (skewness and kurtosis), and the results of the Jarque-Bera test for normality.

Table 7: Descriptive Statistics and Normality Assessment

State	Quarters	Mean	Std. Dev.	Min	Median	Max	Skewness	Kurtosis	JB p-value
Lagos	44	713	325	146	699	1586	0.0642	-0.256	0.97
Ogun	44	537	251	130	622	893	-0.454	-1.39	0.0908

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Oyo	44	388	182	138	402	893	0.453	0.00343	0.438
Ondo	44	303	142	109	302	704	0.865	0.691	0.0267
Osun	44	292	153	78	280	687	0.865	0.197	0.0474
Ekiti	44	70.8	44.5	19	61	270	2.37	7.33	0.001

Source: *Author's computation (2025) using R statistical software*

Table 7 presents the descriptive statistics and normality assessment of quarterly road traffic accident counts across the six states of Southwest Nigeria: Lagos, Ogun, Oyo, Ondo, Osun, and Ekiti, over the study period. The results provide insights into the central tendency, dispersion, and distributional characteristics of accident occurrences in each state.

Central Tendency and Dispersion: Lagos consistently recorded the highest average number of road crashes per quarter (Mean = 713, SD = 325), indicating its position as the most accident-prone state in the region, likely due to its dense population, high vehicle volume, and extensive urban road network. Ogun followed with a mean of 537 accidents per quarter (SD = 251), while Oyo reported a mean of 388 (SD = 182). The remaining states, Ondo (Mean = 303, SD = 142) and Osun (Mean = 292, SD = 153), showed moderate accident frequencies with comparable variability. Ekiti, in contrast, exhibited the lowest quarterly average (Mean = 70.8, SD = 44.5), suggesting substantially lower traffic intensity and road exposure levels compared to its counterparts.

Distributional Characteristics (Skewness and Kurtosis): The skewness values reveal that Lagos (0.0642), Oyo (0.453), Ondo (0.865), and Osun (0.865) possess positively skewed distributions, implying that occasional quarters experienced unusually high accident counts above the state's typical range. Ogun, with a negative skew (−0.454), shows a reverse pattern where accident counts were more frequently below the mean. Notably, Ekiti exhibits an exceptionally high positive skew (2.37), reflecting the presence of several quarters with minimal accidents and a few extreme outlier periods.

The kurtosis statistics indicate the degree of peakedness in the distributions. Lagos (−0.256) and Oyo (0.003) are approximately mesokurtic, suggesting distributions close to normality. Ogun (−1.39) shows a platykurtic distribution, implying a flatter curve with fewer extreme deviations, while Ondo (0.691) and Osun (0.197) are slightly leptokurtic, reflecting moderate clustering around the mean. Ekiti's extremely high kurtosis (7.33) indicates a sharply peaked distribution dominated by rare extreme values.

Normality Assessment (Jarque–Bera Test): The Jarque–Bera (JB) p-values reveal that Lagos ($p = 0.97$), Ogun ($p = 0.0908$), and Oyo ($p = 0.438$) do not significantly deviate from normality, suggesting their distributions approximate a Gaussian pattern. Conversely, Ondo ($p = 0.0267$), Osun ($p = 0.0474$), and Ekiti ($p = 0.000$) exhibit significant departures from normality at the 5% level, primarily driven by their higher skewness and kurtosis levels.

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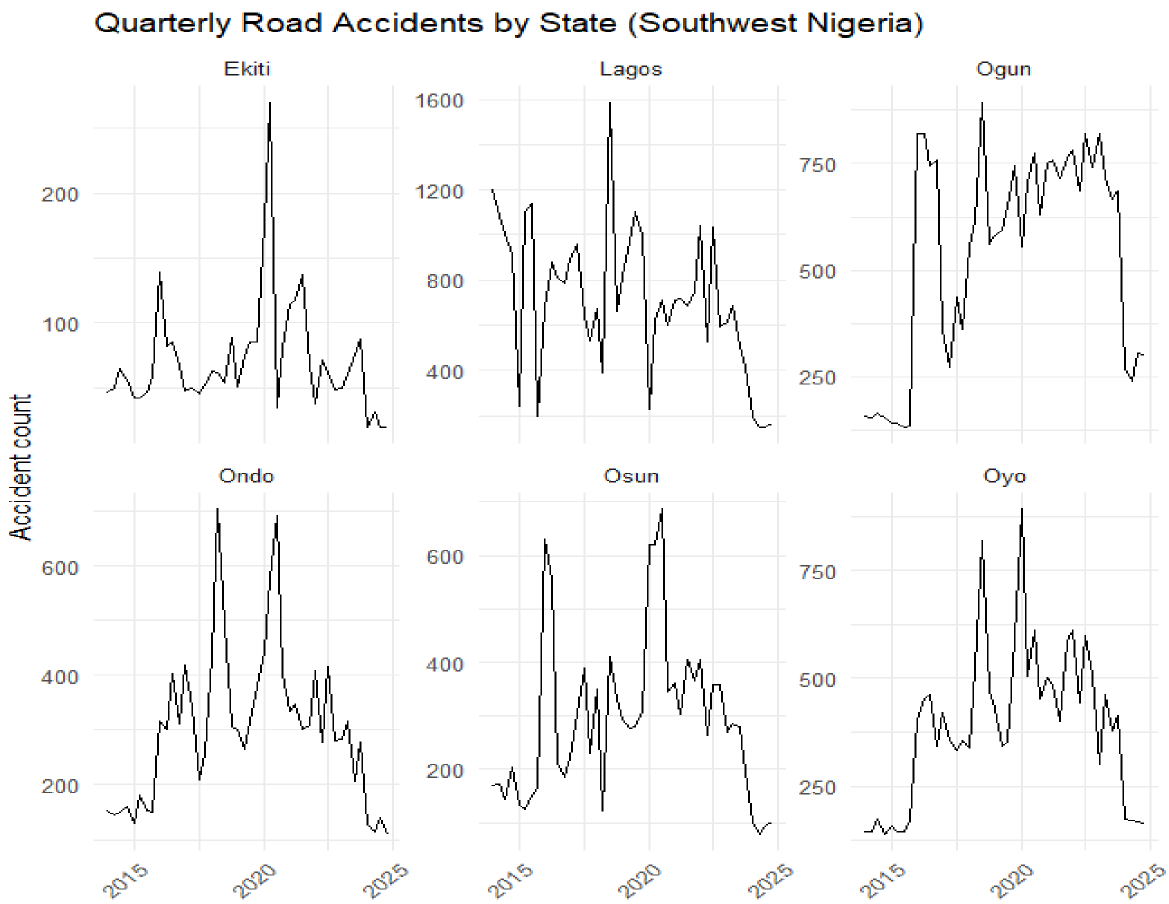
Figure 7. Quarterly Road Accident by State (Southwest Nigeria)



Trend of Total Road Traffic Accidents in Southwest Nigeria (2015-2024)

The line plot in figure 7 below illustrates the overall trend of road traffic accidents across all six states in Southwest Nigeria over a ten-year period, from 2014 to 2024. The trend shows significant seasonal fluctuation, with regular peaks and troughs occurring within each year, which likely correspond to specific quarters (e.g., higher accidents in Q4 during holiday seasons). There appears to be a slight overall upward trend in the number of accidents across the decade, as the peaks and troughs gradually reach higher levels towards the end of the period (2022-2023) compared to the beginning (2014-2015). A notable sharp decline in accidents is visible around 2020, which coincides with the COVID-19 pandemic and associated lockdowns and travel restrictions that significantly reduced vehicular movement. The plot shows a strong recovery in accident numbers post-2020, with counts quickly returning to and eventually exceeding pre-pandemic levels, suggesting a return to normal or increased travel volumes.

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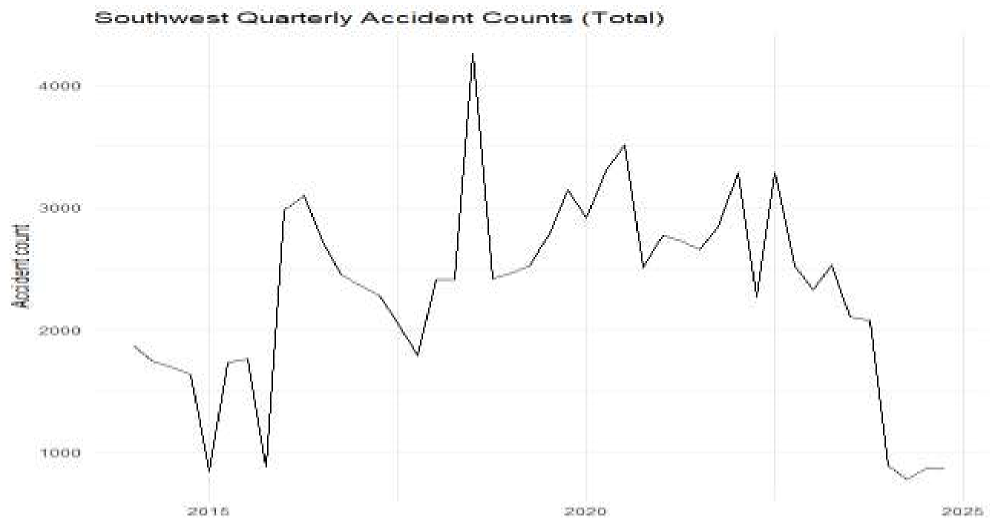
Figure 8. Trend of Total Road Traffic Accidents in Southwest Nigeria (2015-2024)



Seasonal-Trend Decomposition of Quarterly Accident Counts in Southwest Nigeria

The seasonal-trend decomposition in Figure 9 reveals the three fundamental components underlying the quarterly accident counts in Southwest Nigeria from 2014 to 2024. The trend component shows a pronounced long-term pattern, beginning with a period of stability from 2014 to early 2020. This is followed by a sharp, significant decline that coincides precisely with the COVID-19 pandemic and associated lockdowns, which drastically reduced mobility. A strong and steady recovery is observed post-2020, with accident numbers not only returning to pre-pandemic levels but rising to a new, higher plateau by the end of the period, indicating a significant overall increase in accidents over the decade.

The seasonal component exhibits a consistent and predictable pattern that repeats every year. This stable, regular cycle is characterized by a distinct peak and trough within each year, underscoring the strong influence of recurring annual factors such as holiday travel during festive periods, weather cycles like the rainy season, and agricultural calendars on accident frequency.

The remainder component, which captures the irregular noise or random effects after removing the trend and seasonality, is relatively small in scale. The absence of large, persistent outliers in this residual series indicates that the STL model has effectively captured the dominant systematic patterns, the strong trend and seasonality leaving behind only minor, unexplained variations.

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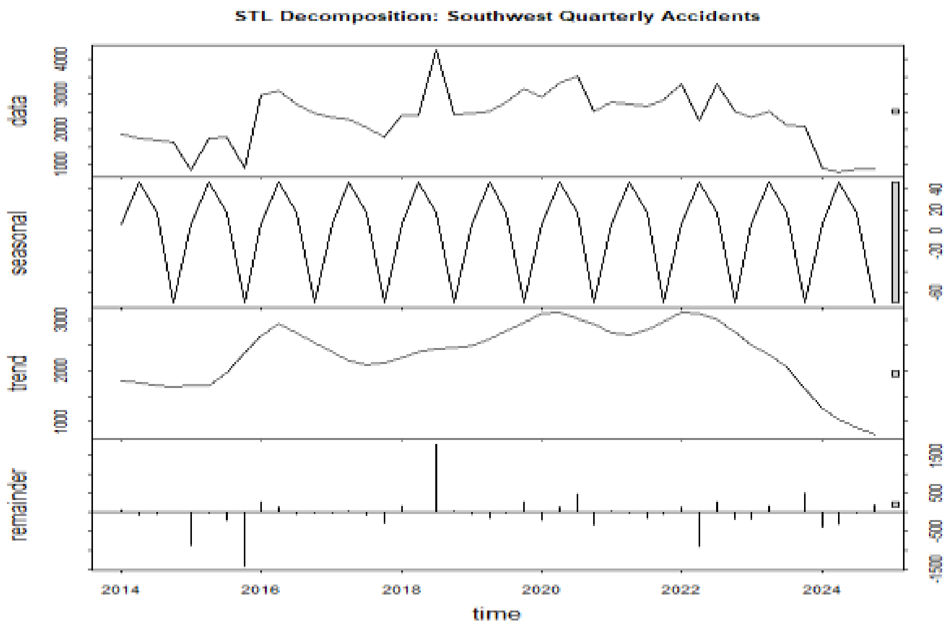
Figure 9. STL Decomposition: Southwest Quarterly Accident



Stationarity Testing of ADF Test Results

Table 8: Stationarity testing of Augmented Dickey-Fuller (ADF) of Road Crash Cases in Southwest Nigeria

Test Statistic	*Lag Order*	*P − value*	*Alternative Hypothesis*
−0.97924	3	0.9302	*Stationarity*

Source: *Author's computation (2025) using R statistical software*

The results presented in Table 8 summarise the outcome of the Augmented Dickey–Fuller (ADF) test applied to the quarterly road crash time series data for Southwest Nigeria between 2014 and 2024. The ADF test is conducted to assess whether the series exhibits stationarity, a crucial assumption for time series modelling such as ARIMA.

The reported test statistic of −0.97924 indicates that the series is not sufficiently negative to reject the null hypothesis of non-stationarity. In the ADF framework, more negative test statistics provide stronger evidence against the null hypothesis that the series contains a unit root. However, since this calculated value is far above the common critical thresholds (e.g., −3.45 at the 5% level), the null hypothesis cannot be rejected.

The lag order of 3 denotes that three lagged differences were included in the model to control for autocorrelation, ensuring a more reliable inference about the stationarity of the series. The p-value of 0.9302 is considerably higher than conventional significance levels (1%, 5%, or 10%), confirming the failure to reject the null hypothesis.

Consequently, the result implies that the quarterly road crash series is non-stationary in its level form, suggesting that the mean and variance of the series vary over time. This non-stationarity

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indicates that shocks or fluctuations in road crash occurrences persist rather than dissipate over time. Therefore, it is appropriate to apply differencing or transformation techniques such as first differencing to achieve stationarity before proceeding with ARIMA modelling and forecasting.

Post-Differencing Stationarity Test (ADF Test on Differenced Series)

Table 9: Augmented Dickey–Fuller (ADF) Test after First Differencing of Road Crash Cases in Southwest Nigeria

$Test\ Statistic$	$Lag\ Order$	$P-value$	$Alternative\ Hypothesis$
-4.7459	3	0.01	$Stationarity$

Source: *Author's computation (2025) using R statistical software*

After differencing the quarterly road crash series once, the Augmented Dickey–Fuller (ADF) test was re-applied to confirm whether the transformation successfully induced stationarity. The post-differencing result in Table 9 shows a Dickey–Fuller statistic of −4.7459, which is considerably more negative than the critical threshold (approximately −3.45 at the 5% significance level). This provides strong evidence against the null hypothesis of non-stationarity.

The lag order of 3 ensures that serial correlation in the residuals is adequately accounted for, enhancing the reliability of the test outcome. The p-value of 0.01 indicates statistical significance at the 1% level, confirming that the null hypothesis can be rejected in favor of the alternative hypothesis of stationarity.

Hence, the first differencing successfully transformed the series into a stationary process, satisfying the key requirement for subsequent ARIMA model estimation. This implies that the mean and variance of the differenced series remain stable over time, and shocks to the system now have only temporary effects rather than persistent ones.

Model Comparison Summary

Table 10: Model Comparison Summary

Model	**AIC**	**RMSE**	**MAE**	**MAPE**
ARIMA(2,0,0)	696.34	599.16	450.19	24.95
ETS	736.83	609.62	441.53	23.95

Source: *Author's computation (2025) using R statistical software.*

Table 10 presents the comparative performance of the ARIMA(2,0,0) and ETS models used to forecast quarterly road crash cases in Southwest Nigeria. The ARIMA(2,0,0) model recorded a lower Akaike Information Criterion (AIC = 696.34) relative to the ETS model (AIC = 736.83), signifying a better model fit and parsimony in capturing the underlying data structure. While the ETS model achieved marginally lower MAE (441.53) and MAPE (23.95%) values indicating slightly better short-run predictive accuracy the ARIMA(2,0,0) model provided the lowest AIC and comparable error levels, suggesting overall superior balance between goodness of fit and forecasting reliability. Therefore, the ARIMA(2,0,0) model was selected as the

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preferred specification for forecasting future crash trends, as it optimally captures both the autocorrelation structure and temporal dynamics of the quarterly series, while maintaining acceptable predictive performance.

Auto-Regressive Integrated Moving Average

Table 11: Estimated ARIMA (2,0,0) Model and Diagnostic Statistics

Parameter	Coefficient	Std. Error	t-Statistic
AR(1)	0.4751	0.1436	3.31
AR(2)	0.2584	0.1497	1.73
Mean	2166.661	324.5201	6.68

Panel B: Model Fit and Forecast Accuracy

Statistic	Value
Log Likelihood	-344.17
AIC	696.34
AICc	697.37
BIC	703.48
Residual Variance (σ^2)	385,259
RMSE	599.16
MAE	450.19
MAPE (%)	24.95
Residual ACF (Lag 1)	-0.0103

Source: *Author's computation (2025) using R statistical software.*

The results in Panel A indicate that the ARIMA (2,0,0) model adequately captures the temporal dependence in the series, as the first autoregressive term is positive and statistically significant, while the second lag contributes moderately to the model dynamics. The estimated mean suggests a relatively high average level of road accident occurrences over the study period. The positive and statistically significant autoregressive coefficients (AR (1) = 0.4751 and AR (2) = 0.2584) imply that previous accident levels strongly influence current crash occurrences, reflecting persistence in road safety patterns. The mean term (2166.66) denotes the long-term average of quarterly road accidents around which short-term fluctuations occur. The standard errors of the parameters are relatively small, confirming estimation precision and model stability.

Panel B shows that the model provides a good fit to the data, as reflected in the relatively low AIC (696.34) and BIC (703.48) indicate that the ARIMA (2,0,0) structure is parsimonious and well-fitted. The residual variance (σ^2 = 385,259) and error measures (RMSE = 599.16, MAE = 450.19) reveal moderate deviations between observed and predicted values. The MAPE of 24.95% suggests a reasonably accurate predictive performance within the acceptable range for time series models involving socio-economic data. Furthermore, the ACF1 value of -0.0103 shows no significant autocorrelation in the residuals, confirming that the model adequately

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captures the data dynamics without systematic bias. Thus, the ARIMA (2, 0, 0) model is statistically robust and suitable for short-term forecasting of road accident cases, providing a reliable foundation for road safety policy and resource allocation in Southwest Nigeria.

Ljung–Box Test for Residual Independence of the ARIMA (2,0,0) Model

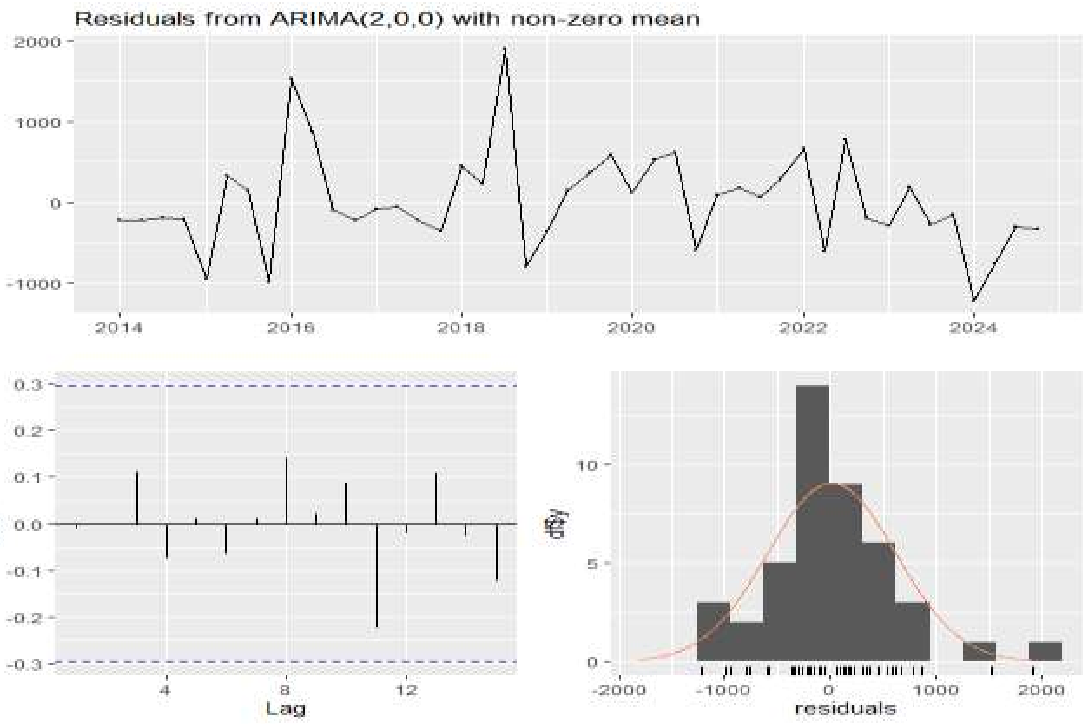
Table 12: Ljung–Box Test for Residual Independence of the ARIMA (2,0,0) Model

Test	Test Statistic (Q*)	Degrees of Freedom (df)	p-value	Decision	Interpretation
Ljung–Box Q Test	2.2571	6	0.8946	Fail to Reject H_0	Residuals are white noise (no autocorrelation)

Source: *Author's computation (2025) using R statistical software.*

Table 12 displays the result of the Ljung–Box test applied to the residuals of the fitted ARIMA (2,0,0) model to verify whether they behave like white noise, an essential condition for model adequacy. The test statistic (Q = 2.2571*) with 6 degrees of freedom yields a p-value of 0.8946, which is much greater than the conventional 0.05 significance level. Consequently, the null hypothesis (H_0) that the residuals are independently distributed cannot be rejected. This indicates that the residuals exhibit no significant autocorrelation, meaning all systematic patterns in the data have been successfully captured by the ARIMA model. In a nutshell, this outcome confirms that the ARIMA (2,0,0) model provides a good fit to the data, with residuals behaving as random noise. The absence of serial correlation validates the model's reliability for forecasting road accident cases in Southwest Nigeria and demonstrates that no important dynamics have been left unexplained.

Figure 10. Residual from ARIMA with non-zero mean



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Forecasting for the Next 12 Quarters (3 years)

Table 13: Forecasting for the next 12 quarters (3 years)

Quarter	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2025 Q1	1212.229	416.7798	2007.678	-4.305594	2428.764
2025 Q2	1376.055	495.3796	2256.730	29.178459	2722.931
2025 Q3	1544.392	583.1915	2505.592	74.362870	3014.420
2025 Q4	1666.707	665.3736	2668.040	135.299736	3198.114
2026 Q1	1768.321	740.2688	2796.374	196.050542	3340.592
2026 Q2	1848.208	803.9671	2892.449	251.179250	3445.237
2026 Q3	1912.422	857.8578	2966.987	299.605139	3525.239
2026 Q4	1963.575	902.5110	3024.640	340.817447	3586.333
2027 Q1	2004.473	939.2746	3069.671	375.392785	3633.553
2027 Q2	2037.122	969.2980	3104.947	404.025860	3670.219
2027 Q3	2063.203	993.7064	3132.700	427.548922	3698.858
2027 Q4	2084.032	1013.4696	3154.594	446.748248	3721.315

Source: *Author's computation (2025) using R statistical software*

The results in Table 13 present the forecasts obtained from the ARIMA(2,0,0) model for quarterly road accident cases in Southwest Nigeria over a three year horizon. The point forecasts indicate a steady upward trend, increasing from approximately 1,212 cases in 2025 Q1 to about 2,084 cases by 2027 Q4. This pattern suggests a gradual rise in accident occurrence if existing conditions remain unchanged.

The associated 80 percent and 95 percent confidence intervals provide measures of uncertainty around these projections. For instance, the 95 percent confidence interval for 2025 Q1 ranges from −4.31 to 2,428.76, while that of 2027 Q4 spans from 446.75 to 3,721.32. The widening of these intervals across the forecast horizon reflects increasing uncertainty, which is typical in time series forecasting as the prediction period extends further into the future.

However, the presence of a negative lower bound in the early forecast period has no practical interpretation, as accident counts cannot be negative. In applied terms, such values are truncated at zero, implying that the effective lower bound for 2025 Q1 should be considered zero. This adjustment does not affect the overall interpretation of the model but rather ensures a realistic representation of forecast outcomes.

ARIMA Forecast of Road Accident Cases in Southwest Nigeria (2025 Q1 – 2027 Q4)

The ARIMA model forecast for Southwest Nigeria predicts a stable yet slightly increasing trend in quarterly accident counts over the next three years (2025-2027). The model projects that accident numbers will continue to fluctuate within the historical range observed between 2016 and 2023, indicating a persistence of the existing seasonal pattern and underlying trend.

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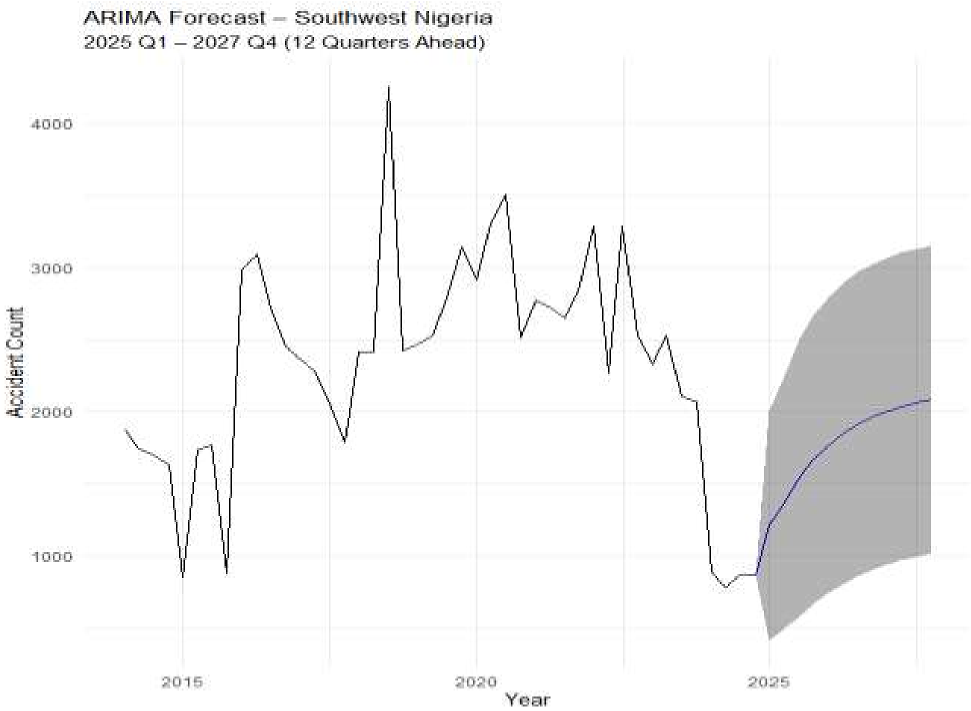
The light blue shaded area around the forecast line represents the 80% prediction interval, showing the range of probable values, while the darker blue band represents the 95% prediction interval, indicating a higher level of uncertainty further into the future. This forecast provides valuable insights for road safety planning and resource allocation throughout the Southwest region for the coming years.

Figure 10. ARIMA Forecast – Southwest Nigeria



CONCLUSIONS AND POLICY RECOMMENDATIONS

This study examined the dynamics of road accidents in Southwest Nigeria using a combined macro-level time series and micro-level accident severity analysis. The time series results revealed a persistent seasonal pattern and long-term upward trend in accident frequencies between 2014 and 2024, with temporary disruptions during the 2020 pandemic. Forecasts from the ARIMA and ETS models projected that road accident occurrences are likely to remain high through 2026, emphasising the need for sustained safety interventions. At the micro level, accident severity was found to be significantly influenced by driver demographics and experience, collision type, and behavioural factors, whereas weather and road surface conditions had a weaker or inconsistent influence. Collectively, these findings underscore that while environmental factors may influence accident frequency, human-related factors primarily determine severity outcomes.

The study concludes that the persistence of high accident rates in Southwest Nigeria is driven by the interaction of structural and behavioural factors. The macro-level time series revealed enduring seasonality and a gradual upward trajectory in crash incidents, while the micro-level results highlighted demographic and collision characteristics as key determinants of severity. Therefore, accident prevention in the region requires not only infrastructure and environmental

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improvements but also interventions targeting human behaviour and enforcement of road regulations.

The following policy recommendations are proposed:

1. Behavioural and Driver-focused Interventions: Strengthen driver education, certification, and re-orientation programmes, particularly targeting male and inexperienced drivers who constitute the highest-risk groups.
2. Enforcement of Road Safety Regulations: Enhance the enforcement of existing traffic laws with strict penalties for reckless driving, over-speeding, and distracted driving, as these are major causes of severe crashes.
3. Seasonal Safety Campaigns: Implement targeted road safety awareness and enforcement campaigns during high-risk periods, especially in the last quarter of the year, when accident frequencies historically rise due to increased travel activities.
4. Data-driven Monitoring Systems: Establish a real-time road safety monitoring and predictive analytics system to forecast high-risk periods and enable proactive resource allocation.
5. Infrastructure and Maintenance: Upgrade and maintain road infrastructure, including proper signage and lighting, especially along major inter-state highways connecting urban centers across Southwest Nigeria.
6. Integration of Accident Databases: Develop a unified national accident data system that links police, hospital, and meteorological records to facilitate predictive modelling and evidence-based policymaking.

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