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ORIGINAL RESEARCH

Forecasting Road Traffic Injuries in North-Eastern Iran: The Effects of COVID-19 and Time Series Analysis (2009–2023)

Toktam Akbari Khalaj[1,*], Taiebe Kenarangi[2], Vahid Fakoor[3], Vahid Ghavami[4], Ali Yazdani[5], Morteza Lotfi[5], Negar Sangsefidi[4,*]

[1]Department of Statistics, Emergency Medical Services, Mashhad University of Medical Sciences, Mashhad, Iran; [2]Department of Public Health and Social Work, Australian Centre for Health Services Innovation and Centre for Healthcare Transformation, Queensland University of Technology, Brisbane, Queensland, Australia; [3]Department of Statistics, Faculty of Mathematics, Ferdowsi University of Mashhad, Mashhad, Iran; [4]Department of Biostatistics, Social Determinants of Health Research Center, School of Health, Mashhad University of Medical Sciences, Mashhad, Iran; [5]Department of Prehospital Emergency, Emergency Medical Services, Mashhad University of Medical Sciences, Mashhad, Iran

*These authors contributed equally to this work

Correspondence: Negar Sangsefidi, Email n.sangsefidi@gmail.com

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Background: Road Traffic Injuries (RTI) represent a major public health issue in the current century. Examining accident data is essential for developing effective strategies and measures aimed at minimizing these incidents and protecting lives.

Methods: This study investigates the impact of the COVID-19 pandemic on RTI in northeast Iran, particularly in Mashhad, a city characterized by a high number of pilgrims and suburban commuters. We employed Seasonal Autoregressive Integrated Moving Average (ARIMA) models to analyze time-series data collected between 2009 and 2023. The dataset included RTI records from official national sources. The seasonal ARIMA approach was selected to capture seasonal variations, long-term trends, and the effects of pandemic-related mobility restrictions on RTI patterns. All analyses were performed by statistical R software version 4.5.1.

Results: The average monthly RTI decreased from 2385 (95% CI: 2055–2794) in 2019 to 2035 (95% CI: 1707–2362) in 2020. This reduction of approximately 14.8% was statistically significant ($p < 0.05$), highlighting the impact of pandemic-related traffic restrictions on road traffic injuries in Iran. The study employed detailed time series analysis, including seasonal ARIMA modeling, to forecast future RTI trends, which is crucial for informing effective prevention strategies.

Conclusion: The analysis reveals seasonal patterns in RTI data, confirming the presence of non-stationarity. The results indicate a projected upward trend in RTI incidence, driven largely by increased traffic volumes in the post-pandemic period. These findings highlight the urgent need for targeted interventions to address this rising burden. Overall, the study offers valuable insights for policymakers, supporting more effective strategies to improve road safety and help mitigate the ongoing public health challenge posed by RTIs.

Keywords: emergency medical services, COVID-19, time series, road traffic injuries

Introduction

For many years, road traffic fatalities have been acknowledged as a global emergency, ranking among the top causes of death annually. Each year, about 1.19 million individuals lose their lives due to road accidents. Although low- and middle-income countries account for roughly 60% of the world's vehicles, they bear 92% of the fatalities on the roads. The United Nations General Assembly has established a bold goal to reduce by half the worldwide number of deaths and injuries from road traffic accidents (RTA) by 2030.[1] RTI remain a leading cause of trauma globally and represent an increasing public health challenge. Understanding patterns in RTI-related fatalities over recent years and projecting future trends provides essential insights for strategic planning, prevention, and effective control measures.[2] In Iran, the number of fatalities in RTI in 2015 was 32 per 100,000 people, which decreased to 20 per 100,000 people in 2018. However, the number of mortalities in road accidents is still so high that it kills 17,000 and injures more than 350,000 annually.[3]

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Mashhad, home to approximately one million suburban residents and a population of about three million, has the largest suburban population in Iran. Each year, the city welcomes 20 to 25 million pilgrims. Consequently, accidents (particularly RTI) are a significant and inherent aspect of life in this bustling metropolis.[4]

The COVID-19 pandemic has disrupted the world's roads and highway networks to a historic extent. While the world is focused on fighting the COVID-19 pandemic, people continue to die and be injured in RTI on highways due to traffic restrictions.[5] Several governments introduced these restrictions progressively, while others enforced them abruptly, resulting in partial or full quarantines.[6] Meanwhile, traffic collisions continue to be a significant global transportation challenge, resulting in substantial economic burdens, loss of life, and injuries to individuals.[7] A global review of how COVID-19 affected traffic collisions, injury severity, and outcomes highlights reduced traffic volume but notes an increase in risky driving behaviors.[8] Islam et al[9] examined the paradoxical effects of reduced traffic volume during the COVID-19 pandemic. While overall crash numbers declined due to mobility restrictions, the authors reported that riskier driving behaviors emerged, leading to an increase in the severity of accidents. Specifically, fatal crashes rose even as the total number of collisions decreased during the pandemic period.

Since February 2020, Iran has witnessed a 5% decline in road accidents, accompanied by a drop in both injuries and fatalities. Moreover, the number of deaths occurring at the scene or in hospital settings has fallen by 10%.[10] With the onset of quarantine, overall movement declined, and concerns about virus exposure eased. This reduction in mobility led to fewer vehicles on the roads, which decreased the probability of traffic accidents.[11,12]

The outbreak of COVID-19 also resulted in a rise in unemployment, with research indicating that financial stress and economic instability can heighten levels of distraction, frustration, and sleep deprivation. These factors are positively associated with accidents and can potentially contribute to road accidents.[13,14] Therefore, this study aims to model and forecast the impact of the COVID-19 pandemic on RTI in northeastern Iran, using seasonal ARIMA time-series analysis. This approach will help capture seasonal patterns, long-term trends, and post-pandemic changes in RTI incidence, providing evidence-based insights for future road safety interventions.

Materials and Methods

ARMA models are among the most extensively applied approaches in time series analysis, offering robust capabilities for understanding patterns and enhancing forecasting accuracy. This model helps analyze many types of time series data that change over time. It belongs to a group of models called ARIMA, which stands for Autoregressive Integrated Moving Average using three key parameters: *p, d*, and *q*. Because most series are non-stationary, they have many applications in statistical analysis. In terms of the backshift B notation, these series are defined as follows:

$$\emptyset(B)\nabla^{d}y_t = \theta(B)e_t,$$

where e_t is a mean zero white noise and variance σ_e^2, and

$$\emptyset_p(B) = \left(1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p\right),$$

$$\theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q\right).$$

Box and Jenkins introduced ARIMA models in their seminal 1970 work, and these models are commonly denoted as $ARIMA(p, d, q)$.

In practice, most time series consist of a seasonal component that repeats each S observation. S indicates the length of the seasonal period, and most time series have a seasonal component. Box and Jenkins generalized the ARIMA model to investigate seasonality and defined the general seasonal model as follows:

$$\emptyset_p(B)\Phi_P(B^s)\nabla^{d}\nabla^{D}y_t = \theta_q(B)\Phi_Q(B^s)e_t,$$

where

$$\Phi_P(B^s) = \left(1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_P B^{Ps}\right),$$

$$\Theta_Q(B^s) = \left(1 - \Theta_1 B^s - \Theta_2 B^{2s} - \ldots - \Theta_Q B^{Qs}\right).$$

The model is presented as a seasonal ARIMA model, denoted as $ARIMA(p, d, q)(P, D, Q)_S$.[15,16]

Model Identification

Time series modeling is a structured process that begins with identification visually and statistically examining the data for trends, seasonal patterns, and variance instability.[16–18] To achieve stationarity, Box-Cox transformations address non-constant variance, while differencing addresses a non-stationary mean. Following these adjustments, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are analyzed to identify the model's structure. Significant cut-offs in these plots suggest either a Moving Average (MA) or Autoregressive (AR) model for non-seasonal components, with seasonal patterns examined at seasonal lags. If a pure model is not evident, a mixed ARMA model is considered. The final step is the diagnostic assessment of the chosen model's adequacy. This standard methodology, as outlined in the literature, was applied to the RTI data.[16,19]

Check the Suitability of the ARIMA Model

For time series modeling, the data were split into training and testing sets to enable both model fitting and evaluation of predictive performance. Model suitability was assessed using the training dataset.

To establish stationarity—a prerequisite for Box-Jenkins modeling—the Augmented Dickey–Fuller (ADF) test is used for non-seasonal unit roots, while the HEGY test is applied for series with seasonality.[20,21] Once stationarity is achieved, candidate models are identified and their parameters estimated. Model adequacy is then diagnostically checked through residual analysis (testing for independence, normality, and constant variance) and by comparing nested models. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), along with Mean Squared Error (MSE), are used to select the optimal model from competing candidates. The final validated model is employed for forecasting future values based on its fitted historical pattern.[3,20,22–24]

Measures of Accuracy

In this subsection, we introduce measures of accuracy based on testing data. Here, the best-fitting model was selected based on accuracy metrics and was checked to ensure it did not overfit the data. The accuracy of the models was evaluated using three standard criteria: the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE), defined by equations (1), (2), and (3), respectively.[15]

$$MAPE = \frac{1}{n}\sum\nolimits_{i=1}^{n}\frac{e_t}{y_t} * 100. \tag{1}$$

$$MAE = \frac{\sum\nolimits_{i=1}^{n}|e_t|}{n}. \tag{2}$$

$$RMSE = \sqrt{\frac{\sum\nolimits_{i=1}^{n} e_t^2}{n}}. \tag{3}$$

Here e_t is a model's residuals.

Data Sources

Numerous developing countries, such as Iran, are grappling with significant traffic accident challenges. Forecasting RTI has emerged as a critical component in establishing effective safety targets. Accordingly, this study seeks to construct predictive models and generate forecasts for monthly RTI trends in northeastern Iran. In this study, after obtaining official permissions, the data was extracted from the pre-hospital emergency automation system from January 2009 to December 2023, which is related to the number of RTIs at EMS. The sample size was 380106 injuries from traffic accidents. Data has gathered by census method. Inclusion criteria included all traffic accident injuries that were transferred to healthcare, or treated, and released at the scene, and exclusion criteria included death before the ambulance arrived and incomplete documentation in the pre-hospital emergency file. Data were registered and entered into the EMS automation system by EMS at the scene. Each case was defined and coded according to the country's EMS guidelines.

Time series analysis was utilized to assess the trend in the number of RTI. Time series models are often easier to predict and can be used more successfully to make future decisions and policies.[19]

Conceptual Framework

For time series modeling (Figure 1), the RTI dataset was divided into a training set (2009–2019, 70%) and a testing set (2020 onward, 30%) to ensure both model fitting and predictive accuracy. We applied the Box-Jenkins methodology for ARIMA modeling, which involves four key stages using the training data: identification, estimation, model checking, and forecasting. The testing set was subsequently used to evaluate the model's predictive accuracy.

Result

Descriptive Trends in RTI (2009–2023)

The data of RTI in EMS, which were collected from the EMS automation system of Mashhad from January 2009 to the end of December 2023. Figure 2 shows the time series in RTI at EMS, the highest number of injuries was 3785 in July 2023, and the lowest was 1071 in February 2014. From 2009 to 2010, we witnessed an increase in RTI, while from 2011 to the end of 2014, this number decreased. The incidence of injuries showed a consistent upward trend over the period 2015 to 2019, reaching 40%. In 2020, due to the epidemic of COVID-19, this number decreased by 14.8%, and after that, the RTI increased. The average monthly RTI fell from 2385 (95% CI: 2055–2794) in 2019 to 2035 (95% CI: 1707–2362) in 2020, with the decline being statistically significant ($p < 0.05$). These findings support the conclusion that COVID-19 related restrictions significantly reduced RTI.

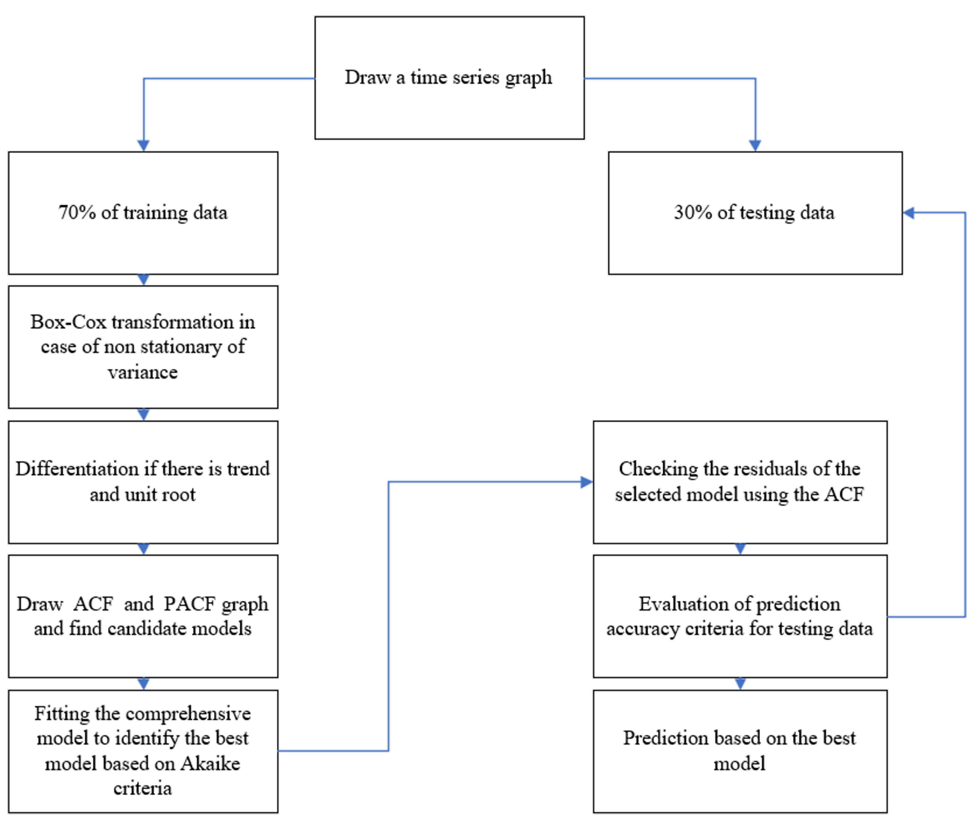

Figure 1 Stages of Time Series Modeling for RTI.

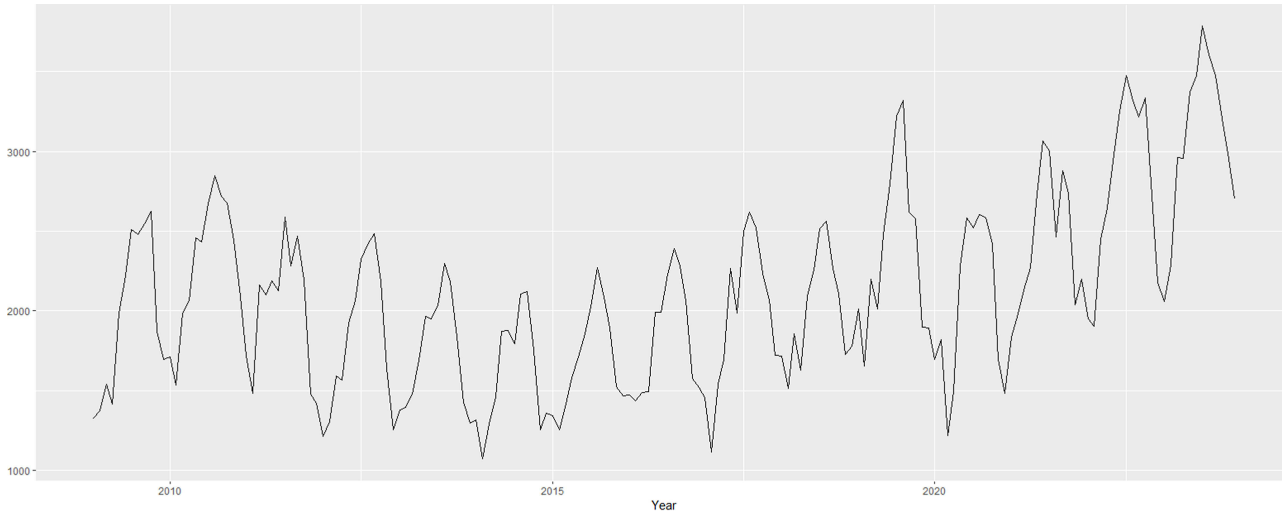

Figure 2 The time series plot of RTI at EMS from 2009 to 2023.

Stationarity and Seasonality Testing

Figure 3 shows the decomposition of the RTI time series into its trend, seasonal, and random components. The ACF plot in Figure 4 confirms the presence of a strong seasonal pattern, with a significant peak at lag 12. This indicates a recurring annual cycle in the injury data.

The Box-Cox transformation suggested an optimal λ of 0.42. However, as its confidence interval included 1, a transformation for variance stabilization was deemed unnecessary. Subsequently, the Augmented Dickey–Fuller test ($p = 0.17 > 0.05$) indicated a non-seasonal unit root, confirming that first-order differencing was required to achieve stationarity in the mean (Table 1).

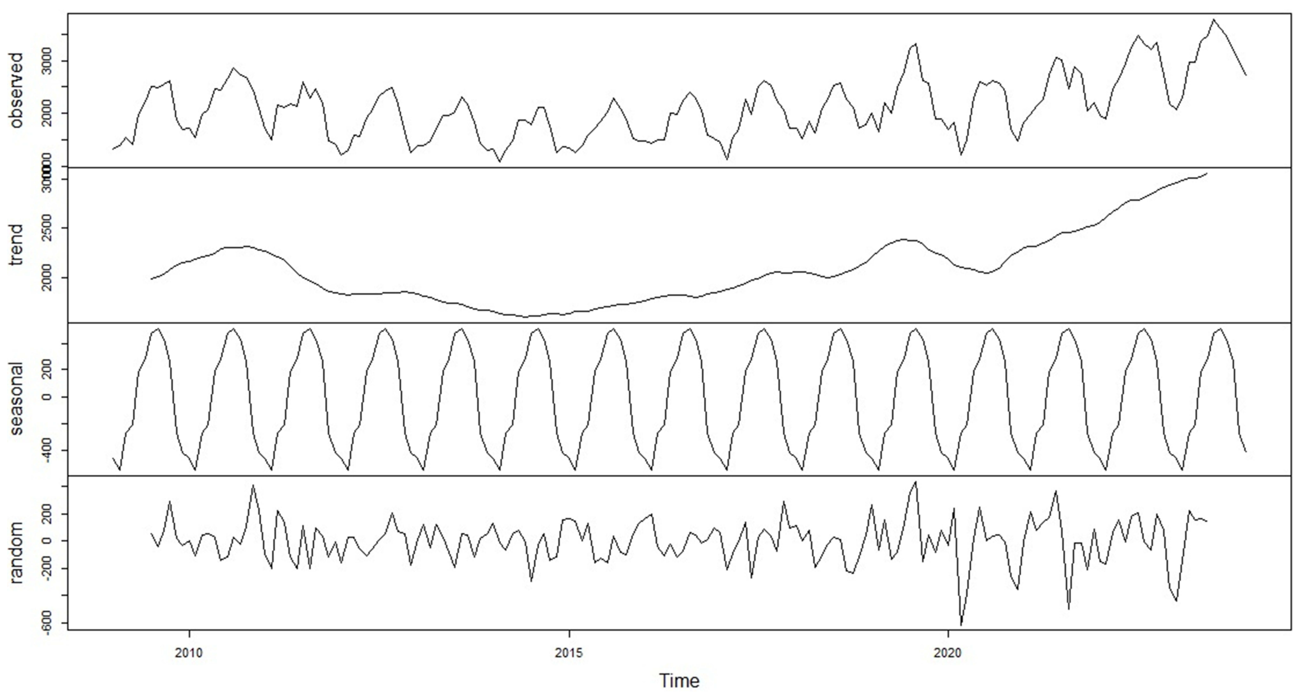

Figure 3 Decomposition of the number of RTI.

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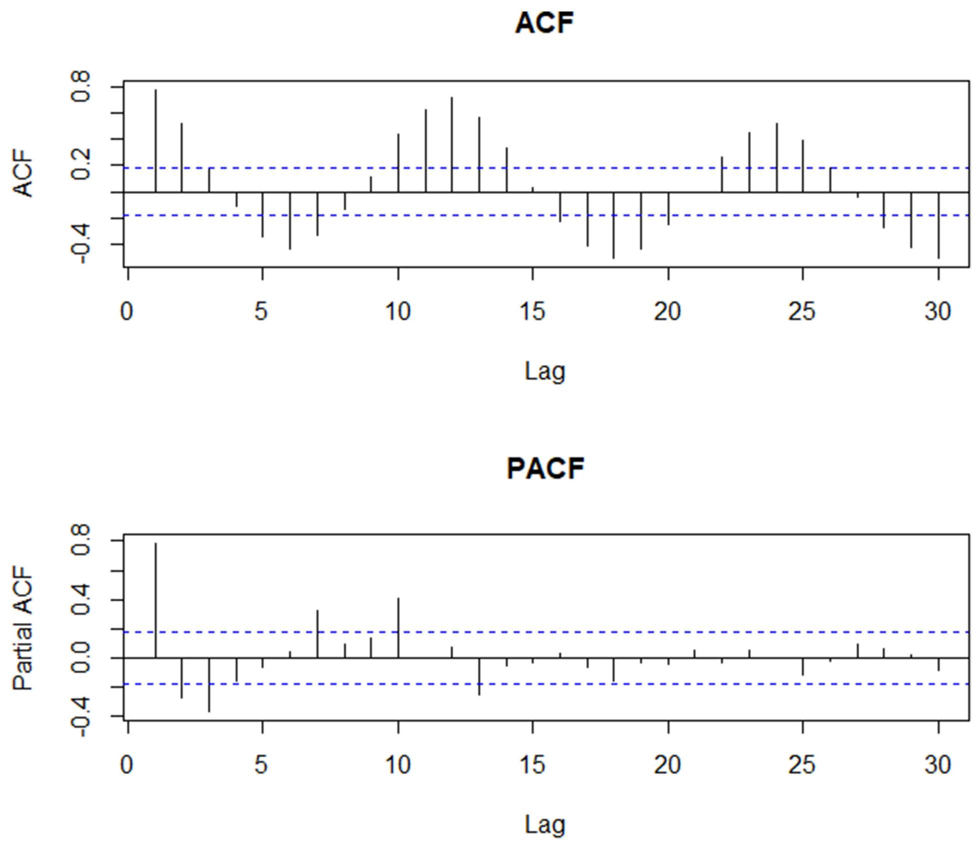

Figure 4 ACF and PACF of RTI. The ACF plot shows autocorrelation in the time series. Significant spikes at lag 12 indicate strong seasonality with a 12-month period in the number of RTI.

The HEGY test was used to examine the seasonal unit root. As can be seen in Table 2, the presence of both a non-seasonal unit root (at zero frequency) and a seasonal unit root at the two-month cycle (frequency π). Additional tests across other seasonal frequencies (eg, four, six, and twelve months) also supported evidence of seasonal unit roots. Therefore, the results of the HEGY test showed that the time series of the number of RTI included a non-seasonal unit root and a seasonal unit root.

Table 1 ADF Test for RTI Data Training

Test	Statistic	Lag Order	P-value
ADF	−2.97	12	0.17

Table 2 The Results of the HEGY Test

Lag	0	π	$\pi/2$	$2\pi/3$	$\pi/3$	$5\pi/6$	$\pi/6$
	t_1	t_{12}	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
Statistics	−1.49	−2.45	15.33	4.37	8.78	12.15	8.04
p-value	0.727	0.068	0	0.10	0.0036	0.000	0.000
Result	Non-stationary	Non-stationary	Stationary	Non-stationary	Stationary	Stationary	Stationary

Model Selection and Diagnostics

The RTI training data underwent a first-order differencing and first-order seasonal differencing method to effectively eliminate both the trend and seasonality from the original dataset. Based on the training data, four models have been considered:

$$ARIMA(1,0,0)(1,1,0)_{12}$$

$$ARIMA(2,1,0)(1,1,0)_{12}$$

$$ARIMA(3,1,0)(2,1,0)_{12}$$

$$ARIMA(2,1,2)(1,1,1)_{12}$$

That can see in Figure 5 for ACF and PACF of the training time series data. Model diagnostics of the fitted models suggested $ARIMA(2,1,2)(1,1,1)_{12}$ the model was tentatively specified for the training process (Table 3). Figure 6 illustrates the analysis of the residuals of an $ARIMA(2,1,2)(1,1,1)_{12}$ model.

The top panel shows residuals over time (x-axis: Year, and y-axis: residuals value). The ACF plot of the residuals indicates that there are no lags outside the confidence limits, confirming the result of the Ljung-Box test. The bottom-left panel presents the ACF of residuals. The bottom-right panel displays the histogram of residuals with a fitted normal curve.

The Akaike information criterion of the models shows that the lowest value belonged to the$ARIMA(2,1,2)(1,1,1)_{12}$ model Therefore, among the proposed models, this model was chosen as the appropriate model, and the parameters of the model are as shown in Table 4.

Forecasting and Prediction Results

The measures of accuracy of the four selected models are reported in Table 5. As can be seen, the model $ARIMA(2,1,2)(1,1,1)_{12}$ has a lowest RMSE, MAE, and MAPE. Therefore, this model was chosen as the best model among the proposed models. It should be noted that the prediction accuracy criteria are for testing data. After determining the best model to fit the data time series and estimating its related parameters, the series was predicted using the selected $ARIMA(2,1,2)(1,1,1)_{12}$ model.

Figure 7 shows the time series forecast of the number of RTI at EMS for the next 36 months. The red lines correspond to the real data, the dashed blue lines correspond to the fitted data, and the green lines correspond to the predicted values.

The predicted values are reported in Table 6. Based on the results, RTI under the influence of different seasons follow a similar sine-cosine cycle, with an average number of accidents of (3301.14 $\pm$ 414.9) cases, reaching its maximum value of 3928.04 injuries in August 2026. Based on the results, this upward trend implies a substantial increase in EMS workload during peak months, highlighting the need for proactive resource planning and seasonal preparedness.

Discussion

In managing trauma patients resulting from traffic injuries, prompt and precise evaluation is essential, as a significant number of fatalities occur before the arrival of ambulances or shortly after the injury takes place.[25]

Traffic accidents remain a major global health challenge, projected by WHO to become the second leading cause of death and disability worldwide by 2024.[1] Using time-series methods, RTI data from EMS (2009–2023) revealed seasonal variation, with injuries peaking in summer and declining in winter. By integrating these measures, our goal is to reduce the burden of road accidents on society and create a safer road environment in a middle-income country like Iran. But this decrease in the number of accidents did not cause a structural break in the time series. This study was conducted to investigate the impact of COVID-19 on road accidents in Iran. According to the results in the initial months and after the announcement of COVID-19, quarantines and movement restrictions, there was a decrease in the number of accidents and deaths in Iran.[10]

Many studies from different countries showed that pandemic restrictions reduced RTA, but the amount of reduction was not the same everywhere.

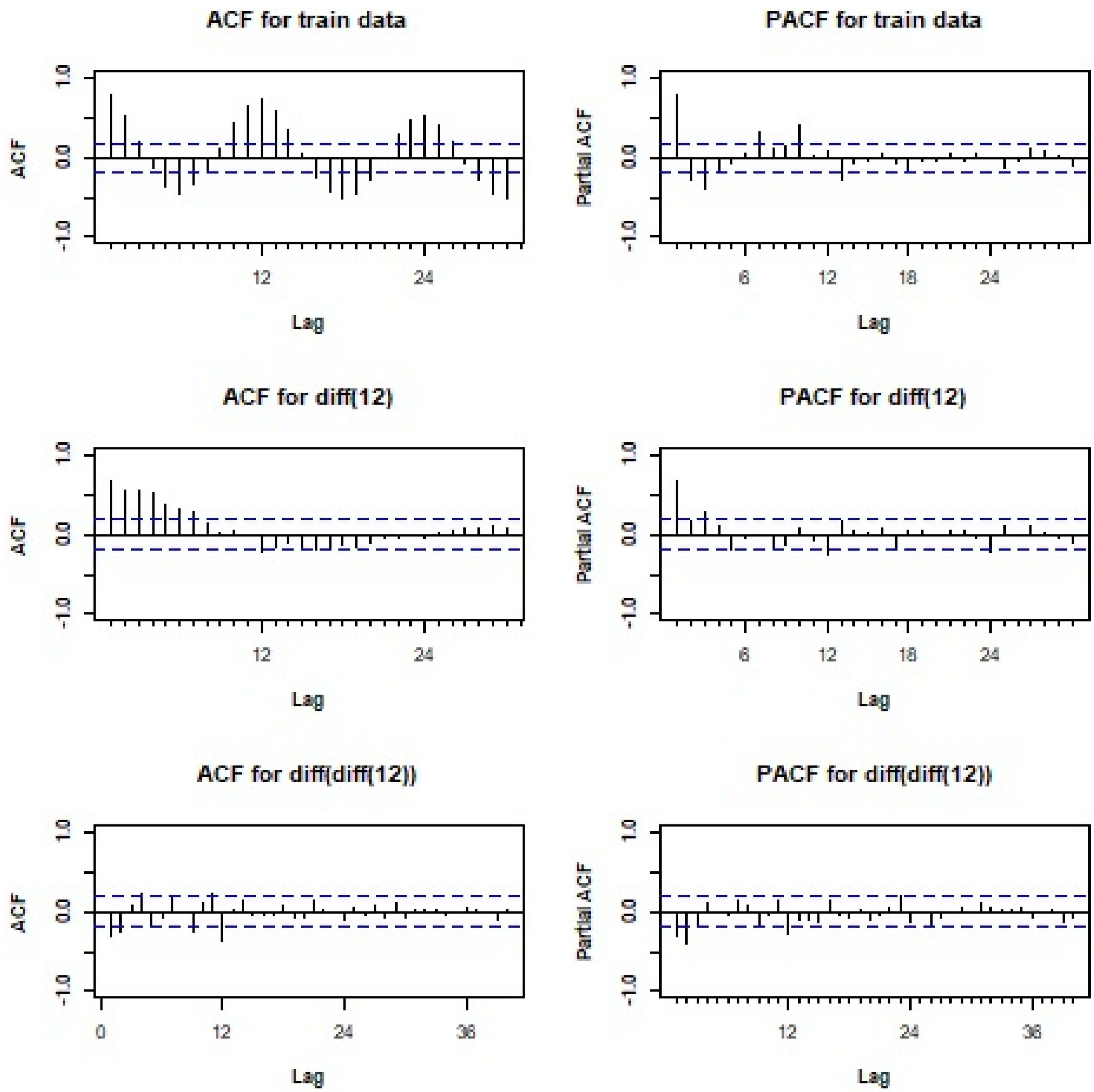

Figure 5 ACF and PACF plots of the training data for RTI: original series (top panels), after first-order seasonal differencing (middle panels), and after both first-order seasonal and non-seasonal differencing (bottom panels). The bottom panels reveal significant spikes at lags 1 and 2 (indicating AR and MA orders of 2) and strong 12-month seasonality at lag 12.

A study in 2022 to assess the influence of COVID-19 on RTI and use the seasonal ARIMA model showed that the pandemic has reduced the number of accidents by a mean of 31% over the analyzed period in Poland. The COVID-19 pandemic significantly affected the performance of the transport sector and its overall intensity. The level of compliance and enforcement of traffic restrictions varied, with stricter enforcement in Poland contributing to a larger reduction.[26] In the study, Sabenorio et. al[27] used 10-year monthly data; they determined and analyzed the behavior of RTA in Metro Manila, Philippines, and created a forecast for the next 5 years using ARIMA modeling. Our result suggests that the total RTA in Metro Manila gradually increased until the first quarter of 2020, then they plummeted and reached their lowest point in April 2020 due to the COVID-19 lockdown. Using Box-Jenkins methodology of ARIMA modeling, this study identified ARIMA (1, 1, 12) as the best model.

Table 3 Fitting More Comprehensive Models of the Number RTI at EMS

Criteria	AR1	AR2	AR3	MA1	MA2	SAR1	SMA2	AIC	BIC	J-B	LBQ
ARIMA (1,0,0) $(1,1,0)_{12}$	0.32*	–	–	–	–	−0.64*	–	1447.66	1355.32	0.27	41.69*
ARIMA (2,1,0) $(1,1,0)_{12}$	−0.42*	−0.34*		–	–	−0.41*		1379.55	1389.72	0.35	29.56
ARIMA (3,1,0) $(2,1,0)_{12}$	−1.12*	−0.97*	−0.56*	–	–	−0.95*	−0.62*	1325.15	1340.41	0.63	14.43
ARIMA (2,1,2) $(1,1,1)_{12}$	−0.11	−0. 28*	–	−1. 33*	−0. 38*	−0. 35*	−0. 99*	1301.56	1319.36	3.59	10.91

Notes: *p < 0.05, ***p < 0.001.
Abbreviations: LBQ, Ljung–Box test; J-B, Jarque–Bera test; AIC, Akaike information criterion; BIC, Bayesian information criterion.

Informal transport and intercity travel remained relatively active in Iran despite restrictions, whereas Poland and the Philippines experienced sharper declines in mobility. The study of Sekadakis et al[7] focuses on the impact of the COVID-19 pandemic on accidents and fatalities in Greece. Using ARIMA time series models, it was shown that the magnitude of

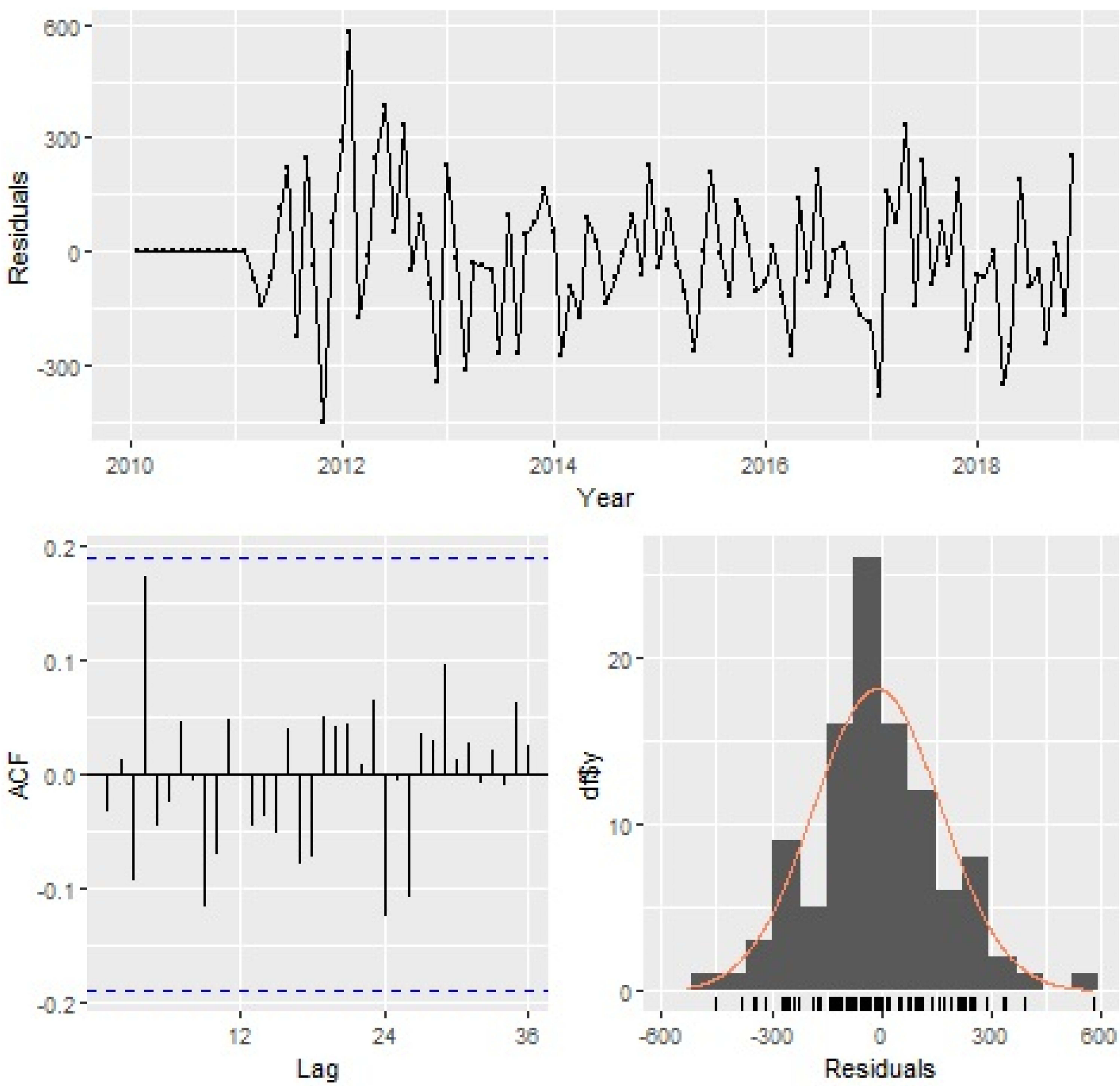

Figure 6 The result of residuals for ARIMA (2,1,2) $(1,1,1)_{12}$.

Table 4 Final Parameter Estimates of ARIMA (2,1,2) × $(1,1,1)_{12}$

Parameter	Coefficient	Standard Error	Z-value	P-value
AR (1)	−0.315	0.130	−8.456	0.01
AR (2)	−0. 286	0.125	−9.285	0.02
MA (1)	−1. 338	0.178	−7.487	0.000***
MA (2)	−0. 384	0.177	2.162	0.03
SAR (1)	−0. 354	0.108	−3.254	0.001
SMA (2)	−0. 999	0.180	−5.551	0.000***

Note: ***$p < 0.001$.

Table 5 The Measures of Accuracy of RTI at EMS

Criteria	MAE	RMSE	MAPE
ARIMA (1,0,0) $(1,1,0)_{12}$	194.49	256.88	178.57
ARIMA (2,1,0) $(1,1,0)_{12}$	250.91	323.03	223.87
ARIMA (3,1,0) $(2,1,0)_{12}$	163.17	221.25	174.132
ARIMA (2,1,2) $(1,1,1)_{12}$	127.79	173.47	137.48

COVID-19 led to fewer crashes and injuries in 2020, but road safety performance decreased when traffic volumes were further reduced. The result showed that the first wave of COVID-19 caused a significant reduction in all road accidents. After the release of quarantine measures from the first wave of the spread, an increase in all fall indicators was also observed. However, the third wave of COVID-19, which lasted more than 7 months, also reduced the number of accidents, but not as much as the first wave of the outbreak.[28]

Our findings of summer peaks and winter declines in Iran align with global evidence that seasonal mobility patterns strongly influence accident rates. A study by Shahsavarinia et al[29] showed that RTI have taken on a new face as one of the leading causes of death worldwide, with the COVID-19 pandemic. And they found that there was a relatively high prevalence of road accidents before COVID-19 compared to the pandemic period. The ARIMA models were applied to

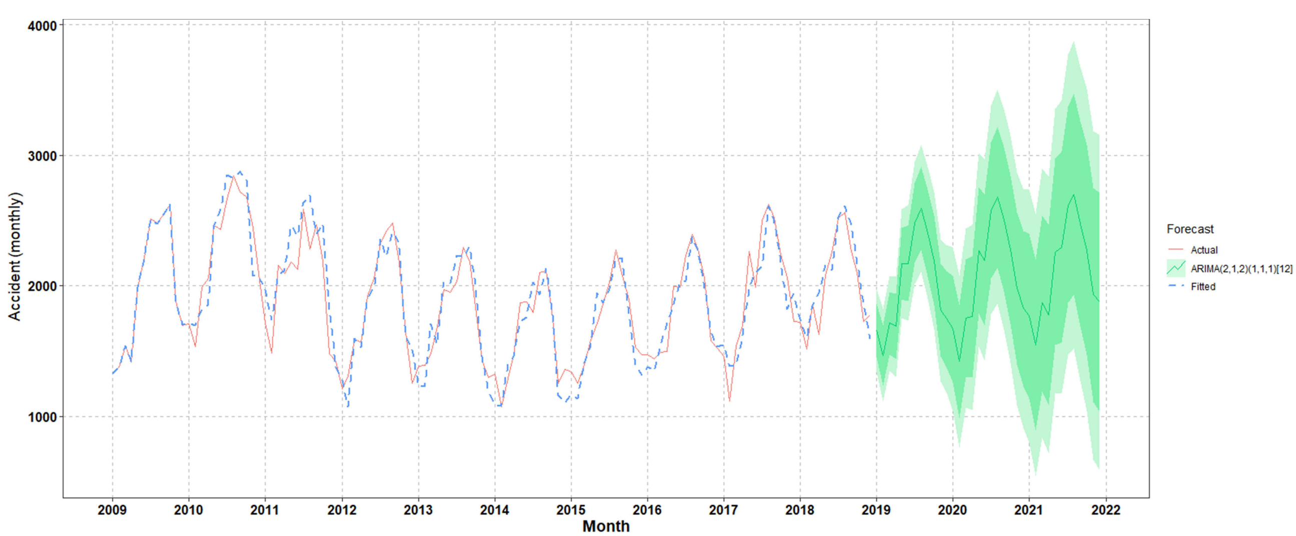

Figure 7 Forecasting RTI at EMS for the next three years.

Table 6 Forecast Values for the Number of Emergency Traffic Accident Injuries 2024–2026

Year/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2024	2583.6	2571.1	2943.1	2988.7	3396.5	3504.2	3742.5	3732.0	3647.9	3458.6	3005.9	2826.2
2025	2774.4	2718.4	3016.3	3065.5	3478.7	3589.9	3815.1	3832.0	3755.5	3580.7	3087.9	2926.4
2026	2886.0	2822.5	3107.7	3157.6	3571.7	3683.6	3906.4	3928.0	3852.9	3680.5	3180.8	3022.5

model the trends and patterns of road traffic accident cases in the Amhara region. The data also reveal that more than half of the accidents involve drivers between the ages of 18–30 years. ARIMA $(2,0,0)(1,0,0)_{12}$ was fitted as the best model for total injury accidents.[30]

Beyond descriptive trends, several studies compared forecasting methods. Agyemang et al[31] found ARIMA $(0,1,1)(1,0,0)_{12}$ provided high accuracy in Ghana compared to Prophet models.

In the study of Hosmer et al[32] which was conducted regarding the number of traffic accidents in Makassar city, the seasonal ARIMA model showed that the number of accidents decreased significantly in 2021.

In Thailand, interrupted time series analysis was combined with ARIMA to capture the impact of multiple pandemic waves.[28] Other studies in China highlighted increases in specific crash types, such as e-bike accidents, despite overall reductions.[33,34]

This study represents the first time-series analysis using EMS data in northeastern Iran, applying seasonal ARIMA modeling to examine long-term patterns in RTI from 2009 to 2023, with particular focus on the impact of the COVID-19 pandemic. The findings demonstrate that government-imposed pandemic restrictions were associated with a temporary decline in RTI, though seasonal patterns persisted without structural breaks in the time series. These reductions diminished over time as mobility gradually returned to pre-pandemic levels.

By leveraging long-term EMS data, the analysis highlights both the persistent burden of RTI and the unique mobility characteristics of northeastern Iran. The strong seasonal components revealed in the modeling approach illustrate the potential of evidence-based forecasting tools to support proactive decision-making. Such models can directly inform road safety strategies (eg, targeted enforcement during high-risk seasons), optimize EMS resource planning (including more effective ambulance allocation and staffing based on predicted injury peaks), and guide post-pandemic traffic management policies aimed at mitigating recurring seasonal risks in Iran.

Future research should expand on advanced forecasting approaches and evaluate the effectiveness of specific policy interventions to further enhance road safety in the region.

Limitations

This study is subject to several key limitations: (1) The reliance on historical data from EMS without external validation restricts the generalizability of the model's precise parameters. (2) The use of EMS records inherently underreports minor injuries managed outside the emergency response system. (3) The model does not account for potential changes in traffic laws or enforcement policies implemented during the COVID-19 pandemic. (4) The seasonal ARIMA framework may not fully capture structural breaks or sudden behavioral changes (eg, pandemic effects).

Conclusions

This is the first study using emergency medical data in northeastern Iran to look at road traffic injuries from 2009 to 2023, especially during COVID-19. Corona restrictions caused a short drop in injuries, but the decrease faded when normal life returned, showing we need ongoing safety measures. The analysis found clear seasonal patterns and shows that forecasting tools can help plan ambulance use, improve road safety, and manage traffic after the pandemic.

These findings give policymakers useful information to better assign resources and act at the right times, while future studies should include more factors to better fight road injuries in countries like Iran.

Abbreviations

RTI, Road Traffic Injuries; RTA, road traffic accidents; ACF, Autocorrelation Function; PACF, Partial Autocorrelation Function; EMS, Emergency Medical Services; AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; MSE, Mean Squared Error; MAPE, Mean Absolute Percentage Error; MAE, Mean Absolute Error; RMSE, Root Mean Square Error.

Ethical Approval

All data used in this study were obtained from anonymized secondary sources provided by the EMS automation system. Before access, all patient identifiers were removed to ensure strict confidentiality. As a result, individual informed consent was not required. This study was reviewed and approved by the Ethics Committee of Mashhad University of Medical Sciences (Approval Code: IR.MUMS.REC.1398.280), and all procedures were conducted by the ethical principles outlined in the Declaration of Helsinki.

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