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Novel application of time-weighted statistical techniques for trend analysis in roadway accident fatalities: A case study from Albania

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Abstract: Road transportation in developing countries is a rapidly growing industry, leading to an increased risk of roadway accidents, which pose significant challenges across social, economic, health, justice, and security dimensions. Fatalities resulting from road accidents remain a global concern, and in Albania, despite a reduction in the number of accidents in recent years, the fatalities per 100,000 population have shown a significant rise compared to previous years. This study presents a novel application of three time-weighted statistical techniques, commonly used in quality control processes, to detect sustained changes in fatality trends due to roadway accidents over a 120-month period. The study not only compares the performance of the three designed control chart schemes but also highlights their sensitivity in detecting small shifts from the mean levels, with the Moving Average Technique being the most sensitive. Moreover, the points of process change are clearly identified and effectively located by all three techniques. The findings demonstrate the utility of these methods as diagnostic tools for identifying critical trends and evaluating the effectiveness of interventions aimed at reducing roadway fatalities in Albania. This research introduces an innovative approach to trend analysis in roadway accident fatalities and provides a framework for enhancing road safety management strategies in developing countries.

Keywords: *Albania, Roadway accidents, Time-Weighted Techniques, Trend fatalities.*

1. Introduction

The road transport sector is expanding rapidly in developing nations, contributing to a rise in traffic accidents, which pose significant challenges across multiple dimensions, including social, economic, health, legal, and security concerns [1, 2]. As an integral component of the national transportation network, the road transport industry must enhance its capacity to ensure safety, efficiency, and seamless operations, supporting economic and regional development. The increasing population has led to a surge in vehicle ownership, a rise in road accidents [3, 4] and, in recent years, a decline in fatality rates, particularly in developing nations [5-7]. Although these countries account for nearly 60% of the world's vehicles, they experience 93% of global road accident fatalities [8]. To mitigate accident rates, it is essential to improve road infrastructure design and integrate safety measures into transportation planning [9]. Road traffic incidents should be treated as an urgent issue requiring immediate action to minimize adverse impacts on health, society, and the economy [10].

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Fatalities and injuries resulting from roadway accidents present a serious problem for both developed and developing nations. Current trends indicate that by 2030, road accidents could become the fifth leading cause of death worldwide [11, 12].

The World Health Organization (WHO) reports that nearly 90% of road traffic deaths occur in low- and middle-income countries, even though these regions own only half of the world's motor vehicles. The economic consequences of such accidents are severe. Data further reveal that approximately 1.3 million individuals die annually due to road accidents, while an additional 20 to 50 million suffer injuries across the globe [12, 13]. Addressing the challenges of forecasting traffic accidents is crucial for public safety, and research has emphasized various contributing factors. Tackling these issues plays a fundamental role in promoting road safety and fostering a more sustainable transport sector in developing nations beyond 2030 [14, 15]. Many traffic collisions are preventable, as they stem from specific risk factors associated with driver behavior, vehicle conditions, road design, and environmental elements [16, 17]. Key causes of road accidents include speeding, impaired driving due to alcohol, and non-compliance with safety measures like seatbelt use, helmets, and child restraints [18-21]. Other influential factors include driver age, time of travel, and geographical location, all of which significantly affect accident rates [18, 21]. Regardless of a country's level of development, traffic crashes remain one of the leading causes of mortality [22, 23]. Given the inevitability of road accidents, economic projections suggest that global losses due to fatal and non-fatal traffic incidents could reach approximately $1.8 trillion USD between 2015 and 2030, underscoring the magnitude of this global issue [24, 25]. Road traffic fatalities result from a combination of complex factors, making it difficult to attribute them to a singular cause. However, refining accident prediction models is crucial for strengthening traffic safety strategies [26, 27]. In Europe, Albania has exhibited a rising trend in fatal traffic collisions [28]. Recent statistics position the country eighth in terms of road traffic mortality rates per 100,000 people [29]. The Albanian Statistical Institute [30] indicates that while the overall number of accidents has declined in 2024, the fatality rate per 100,000 individuals has significantly increased. Male fatalities surpass female fatalities, and drivers are more frequently involved in fatal crashes than pedestrians. The age group most susceptible to accidents falls between 25 and 34 years, with drivers being the primary contributors to collisions [31]. This study aims to evaluate trends in road accident fatalities in Albania, which will support future projections and the formulation of effective preventive policies. Numerous studies worldwide have examined road traffic fatality patterns and assessed the success of various intervention strategies. Time series models have been widely employed for these analyses [32-36].

Nevertheless, long-term data collection is necessary to improve the accuracy of time series models [37]. Consequently, some researchers have utilized Time-Weighted statistical techniques to refine projections of traffic-related fatalities [38-40]. These methods are also extensively applied in modern industries for monitoring and controlling service and manufacturing processes Zhao, et al. [41]; Chamalwa, et al. [42] and Aslam, et al. [43]. Jamal, et al. [38] and Adekeye and Aluko [39] implemented statistical monitoring approaches for real-time highway safety surveillance using three years of crash data from rural highways in Saudi Arabia. Through an extensive simulation-based study, they compared the performance of various control charts, focusing on run-length characteristics. Their findings demonstrated that EWMA-type control charts provided superior detection capabilities compared to CUSUM and Shewhart control charts, especially for small and moderate shifts. Furthermore, these monitoring techniques were successfully applied to real-world crash data to validate their effectiveness. A related study by Adekeye and Aluko [39] employed CUSUM control charts to examine fatal traffic accidents in a state in western Nigeria. The control chart successfully identified periods with the highest fatality occurrences, particularly during festive seasons, highlighting the necessity for road authorities to enhance safety measures during these critical times. Braimah, et al. [44] and Shewhart [45] developed and compared CUSUM, EWMA, and Moving Average control charts to detect fluctuations in roadway accident data in Nigeria. The study revealed that CUSUM charts were the most effective in identifying minor deviations in the process mean, surpassing both

EWMA and Moving Average charts. Similarly, Olanrewaju, et al. [40] applied EWMA and CUSUM techniques over a 120-month period to assess daily crash casualties in Osun State, Nigeria. A comparative analysis confirmed that while both methods effectively identified deviations, CUSUM exhibited greater sensitivity. Additionally, both charts accurately detected and highlighted shifts in accident trends.

In this study, CUSUM, EWMA, and Moving Average statistical techniques—commonly employed in quality control processes—were utilized to monitor sustained variations in fatality trends following roadway accident interventions over a 120-month period. This methodology enabled a comprehensive analysis of accident patterns and intervention effectiveness. Table 1 displays the recorded fatality data throughout the study period. The performance assessment of the three control charts confirmed their efficacy in detecting minor deviations from the mean, with the Moving Average technique demonstrating the highest sensitivity. Furthermore, all methods successfully identified and highlighted critical change points in accident trends. These insights provide valuable information for designing strategies to manage and reduce roadway accident fatalities in Albania.

Table 1.
Data on fatalities over the study period.

Months/Years	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
January	19	17	22	13	15	17	22	16	13	11
February	23	21	17	20	9	12	18	16	14	8
March	21	16	16	14	24	10	18	14	19	14
April	27	27	22	14	14	10	12	10	13	20
May	27	26	26	17	14	9	20	19	13	9
June	21	23	12	20	26	16	15	14	18	12
July	18	27	22	18	13	14	13	6	20	9
August	22	25	22	27	22	26	26	14	11	16
September	24	19	17	9	20	24	7	13	18	14
October	18	27	20	16	25	15	14	12	13	19
November	23	15	20	22	21	15	11	9	25	16
December	27	26	16	23	24	13	21	21	15	26

2. Methodology

A critical component of Time-Weighted Control Charts is the use of control limits, which define the acceptable range of variations in the dataset. These limits are not static but instead fluctuate based on the number of subgroups included in the analysis. Subgroups, which represent specific time intervals (e.g., monthly or quarterly accident records), allow for a more refined investigation of trends. The manner in which control limits adjust across different charts depends on how they change in relation to the number of subgroups. This flexibility enables the identification of statistically significant deviations in accident fatality trends over time [46]. By analyzing subgroups, the study seeks to detect periods where fatalities exhibit significant increases or decreases, which may indicate the success or failure of safety interventions. Seasonal variations, such as higher accident rates during holiday periods, are also considered to determine recurring patterns. Furthermore, the analysis assesses whether reductions in fatalities following road safety policies are sustained over time or whether they represent only short-term improvements. Understanding these patterns is crucial for developing long-term strategies to enhance road safety and reduce accident-related deaths. The data for this study were sourced from the Albanian Statistical Institute (INSTAT), which maintains official records on public safety and transportation. The dataset includes annual and monthly counts of roadway accident fatalities, along with demographic details of accident victims such as age, gender, and location. Additionally, the dataset contains records of traffic safety interventions, including law enforcement measures, infrastructure improvements, and public awareness campaigns. This information provides a comprehensive foundation for analyzing fatality trends and assessing the effectiveness of intervention strategies.

To ensure the accuracy and reliability of the dataset, the study incorporated several preprocessing steps before conducting the statistical analysis. Data cleaning was performed to remove inconsistencies and missing values, ensuring that the dataset remained robust and free from errors. Normalization techniques were applied to standardize values across different time periods, making comparisons between years more reliable. Lastly, categorization was used to classify accidents based on factors such as severity, location, and the presence of safety interventions. These preprocessing steps help refine the dataset and ensure that the statistical models produce accurate and meaningful results.

2.1. The CUSUM Statistical Technique

"Cumulative Sum control models were first proposed by Page [47]. The Cumulative Sum control chart is a good alternative when small shifts are important. It is a graphical representation of the trend in the outcome of a series of consecutive procedures performed over time" [39, 47]. Moreover, the CUSUM control chart can be adapted for different states in the country, the entire country, and all countries of the world [39, 44]. Suppose that *X* represents a process characteristic variable of concern and that it obeys a normal distribution $N(\mu,\sigma^2)$, with known mean μ, and standard deviation σ. Without loss of generality, we may suppose that $\mu = 0$ and $\sigma = 1.5$, with $\mu = \delta$ for an out-of-control process. Let $\{x_1, x_2, ..., x_n, \ldots\}$ a series of observations for the process variable, *X* [48].

In particular, the CUSUM statistics are defined as:

$$C_i = \sum_{j=1}^{i} (x_i - \mu_0) \qquad (1)$$

$$C_i^+ = \max\left[0, x_i - (\mu_0 + K) + C_{i-1}^+\right] \qquad (2)$$

$$C_i^- = \max\left[0, (\mu_0 - K) - x_i + C_{i-1}^-\right] \qquad (3)$$

where, the starting values for the statistics are $C_0^+ = C_0^- = 0$.

"The CUSUM control chart is determined by *K* and *H*, and an out-of-control signal is triggered if either one of the two CUSUM charts, C_i^+ and C_i^-, signals. *K* is usually called the reference value (or the allowance, or the slack value), and it is often chosen about halfway between the target μ_0 and the out-of-control value of the mean μ_1 that we are interested in detecting quickly. The process is considered to be out of control if $C_i^+ > H$ for an upward shift or $C_i^- < -H$ for a downward shift [49]. The values of μ_0 and μ_1 are the mean numbers of counts per sampling interval. The reference value K for the CUSUM chart should be chosen close to:"

$$K = \frac{\mu_1 - \mu_0}{\ln \mu_1 - \ln \mu_0} \qquad (4)$$

"The proper selection of these two parameters is quite important, as it has a substantial impact on the performance of the CUSUM. A reasonable value for *H* is four or five times the process standard deviation *σ*. A two-sided CUSUM control chart is encouraged because its properties can easily be obtained by combining the results of the respective one-sided charts used to detect significant increases or decreases, while this approach allows for flexibility in detecting change [39, 50]. If the process remains in control at the target value μ_0 the cumulative sum defined in equation (1) is a random walk with mean zero. However, if the mean shifts upward to some value $\mu_1 > \mu_0$ an upward or positive drift will develop in the Cumulative Sum *Ci*. Conversely, if the mean shifts downward to some μ_1 [50]".

The Upper Control Limit and the Lower Control Limit for the CUSUM control chart are given by Eq.

$$UCL = \max\left[0, C_{i-1}^{+} + x_i - \mu_0\right] > H \tag{5}$$

$$LCL = \min\left[0, C_{i-1}^{-} + x_i - \mu_1\right] < -H \tag{6}$$

2.2. The Exponentially Weighted Moving Average Statistical Technique

"The Exponentially Weighted Moving Average (EWMA) model was derived by JP Morgan in 1989 from a Gaussian distribution, for their risk metrics framework [51]. The EWMA chart is easy to plot and interpret, and its control limits are easy to obtain. Further, the EWMA leads naturally to an empirical dynamic control equation [52]. The EWMA statistic is defined as:

$$Z_i = \left[wX_i - (1-w)Z_{i-1}\right] \tag{7}$$

where $0<w\leq 1$ is a constant. In general, values of w in the interval $0.05\leq w\leq 0.25$ work well in practice, with w=0.05, w=0.10, and w=0.20 being popular choices".

The starting value for the statistic is $Z_0 = \mu_0$

The center line and control limits for the EWMA control chart are given by Equation:

$$UCL = \mu_0 + L\sigma\sqrt{\frac{w}{2-w}} \tag{8}$$

$$LCL = \mu_0 - L\sigma\sqrt{\frac{w}{2-w}} \tag{9}$$

The factor L in equations (6) and (7) is the width of the control limits. In general, the value of L=3 works reasonably well.

2.3. The Moving Average Statistical Technique

The Moving Average statistics of span w at time i is defined as Montgomery [48]:

$$M_i = \frac{X_i + X_{i-1} + \ldots + X_{i-w+1}}{w} \tag{10}$$

The variance of the moving average M_i is:

$$\sigma^2(M_i) = \frac{1}{w^2}\sum_{j=i-w+1}^{i}\sigma^2(x_j) = \frac{1}{w^2}\sum_{j=i-w+1}^{i}\sigma^2 = \frac{\sigma^2}{w} \tag{11}$$

Therefore, if μ_0 denotes the target value of the mean used as the center line of the control chart, then the three-sigma control limits for M_i are:

$$UCL = \mu_0 + \frac{3\sigma}{\sqrt{w}} \tag{12}$$

$$LCL = \mu_0 - \frac{3\sigma}{\sqrt{w}} \tag{13}$$

The control process involves computing the updated moving average M_i as each new observation x_i is recorded. This value is then plotted on a control chart, which features upper and lower control limits determined by equations (10) and (11). If M_i surpasses these predefined control limits, it indicates that the process has deviated from control. Generally, there is an inverse relationship between the size of the shift being monitored and the parameter w; longer-span moving averages are more effective in detecting smaller shifts, though they may respond more slowly to larger shifts.

3. Results

3.1. Intervention of Analysis Performed by CUSUM

"From the data for 120 months, the overall mean per month is $\bar{X}$= 17, and the standard deviation σ=5. Thus, to detect changes in the mean level of accident fatalities during this period, the acceptable mean level is chosen nearer to the current mean level μ_0 = 17 and standard deviation σ=5. Then μ_1 = μ_0 + δσ = 17+1.5 × 5=25.

Using Equation (1), $K = \frac{25-17}{ln25-In17} \approx 21$, and from the rule of $H, H = 20.$ Therefore, an out-of-control signal will be indicated when C_i>20.

The points of change in the process are identified and located on the CUSUM chart in Figure 1. The months when high incidence of roadway accident fatalities is evidenced should be used as a reference point to pay more attention or take precautions on the roads to reduce or eliminate high cases of roadway accident fatalities [44]. The values of CUSUM statistics are computed similarly using Equation (1) over a 120 months period and are presented in Table 2 — Table 11. Using Equation (5) and Equation (6), we computed $UCL = 21.4$ and $LCL = -21.4.$ From calculated values, the road accident fatalities were out of control from the 18th month to the 29th month".

Table 2.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2015.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i-K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	19	-2	-2	0	17.9	19.0
February	23	2	0	0	18.9	21.0
March	21	0	0	0	19.3	21.0
April	27	6	6	6	20.9	22.5*
May	27	6	12	12	22.1	23.4*
June	21	0	12	12	21.9	23.0*
July	18	-3	9	9	21.1	22.3
August	22	1	10	10	21.3	22.3
September	24	3	13	13	21.8	22.4
October	18	-3	10	10	21.1	22.0
November	23	2	12	12	21.4	22.1
December	27	6	18	18	22.6*	22.5*

Table 3.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2016.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i-K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	17	-4	14	14	21.4	22.1
February	21	0	14	14	21.4	22.0
March	16	-5	9	9	21.4	21.6
April	27	6	15	15	20.3	22.0
May	26	5	20	20	21.6	22.2
June	23	2	22	22*	22.5*	22.5*
July	27	6	28	28*	22.6*	22.6*
August	25	4	32	32*	23.5*	22.4
September	19	-2	30	30*	23.8*	22.4
October	27	6	36	36*	22.8*	22.6*
November	15	-6	30	30*	23.7*	22.3
December	26	5	35	35*	21.9	22.5*

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Table 4.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2017.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	22	1	36	36*	22.7*	22.4
February	17	-4	32	32*	22.6*	22.3
March	16	-5	27	27*	21.5	22.0
April	22	1	28	28*	20.4	22.0
May	16	-5	23	23*	20.7	21.8
June	12	-9	14	14	19.8	21.5
July	22	1	15	15	21.5	21.5
August	22	1	16	16	19.0	21.4
September	17	-4	12	12	19.6	21.3
October	20	-1	11	11	19.1	21.3
November	20	-1	10	10	19.2	22.3
December	16	-5	5	5	19.4	21.1

Table 5.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2018.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	13	-8	-3	0	18.7	20.9
February	20	-1	-4	0	17.6	20.8
March	14	-7	-11	0	18.1	20.7
April	14	-7	-18	0	17.2	20.5
May	17	-4	-22	0	16.6	20.5
June	20	-1	-23	0	16.7	20.4
July	18	-3	-26	0	17.3	20.4
August	27	6	-20	0	17.5	20.5
September	9	-12	-32	0	19.4	20.3
October	16	-5	-37	0	17.3	20.2
November	22	1	-36	0	17.0	20.2
December	23	2	-34	0	18.0	20.3

Table 6.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2019.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	15	-6	-40	0	19.0	20.2
February	9	-12	-52	0	18.2	19.9
March	24	3	-49	0	16.4	20.0
April	14	-7	-56	0	17.9	19.9
May	14	-7	-63	0	17.1	19.8
June	26	5	-58	0	16.5	19.9
July	13	-8	-66	0	18.4	19.8
August	22	1	-65	0	17.3	19.8
September	20	-1	-66	0	18.3	19.8
October	25	4	-62	0	18.6	19.9
November	21	0	-62	0	19.9	19.9
December	24	3	-59	0	20.1	20.0

Table 7.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2020.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	17	-4	-63	0	20.9	19.9
February	12	-9	-72	0	20.1	19.8
March	10	-11	-83	0	18.5	19.7
April	10	-11	-94	0	16.8	19.5
May	9	-12	-106	0	15.4	19.3
June	16	-5	-111	0	14.1	19.3
July	14	-7	-118	0	14.5	19.2
August	26	5	-113	0	14.4	19.3
September	24	3	-110	0	16.7	19.4
October	15	-6	-116	0	18.2	19.3
November	15	-6	-122	0	17.5	19.9
December	13	-8	-130	0	17.0	19.2

Table 8.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2021.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	22	21	-109	0	16.2	19.2
February	18	-3	-112	0	17.4	19.2
March	18	-3	-115	0	17.5	19.2
April	12	-9	-124	0	17.6	19.1
May	20	-1	-125	0	16.5	19.1
June	15	-6	-131	0	17.2	18.9
July	13	-8	-139	0	16.8	19.0
August	26	5	-134	0	16.0	18.9
September	7	-14	-148	0	18.0	18.8
October	14	-7	-155	0	15.8	18.8
November	11	-10	-165	0	15.4	18.8
December	21	0	-165	0	14.6	18.7

Table 9.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2022.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	16	-5	-170	0	15.8	18.7
February	16	-5	-175	0	15.9	18.7
March	14	-7	-182	0	15.9	18.6
April	10	-10	-190	0	15.5	20.8
May	19	-2	-192	0	14.4	18.5
June	14	-7	-199	0	15.3	18.5
July	6	-15	-214	0	15.1	18.4
August	14	-7	-221	0	13.3	18.3
September	13	-8	-229	0	13.4	18.3
October	12	-9	-238	0	13.3	18.2
November	9	-12	-250	0	13.1	18.1
December	21	0	-250	0	12.2	18.2

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Table 10.
Computed Cusum, and EWMA, AM Statistics in fatalities of roadway accidents for the year 2023.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	13	-8	-258	0	14.0	18.1
February	14	-7	-265	0	13.8	18.0
March	19	-2	-267	0	13.8	18.0
April	13	-8	-275	0	14.9	18.0
May	13	-8	-283	0	14.5	17.9
June	18	-3	-286	0	14.2	17.9
July	20	-1	-287	0	15.0	17.9
August	11	-10	-297	0	16.0	17.9
September	18	-3	-300	0	15.0	17.9
October	13	-8	-308	0	15.6	17.8
November	25	4	-304	0	15.1	17.9
December	15	-6	-310	0	17.1	17.9

Table 11.
Computed Cusum, EWMA, and AM Statistics in fatalities of roadway accidents for the year 2024.

Months(i)	X_i	X_i-K	$C_i=\sum(X_i\text{-}K)$	C_i	$Z_i= wX_i+ (1 - w)Z_{i-1}$	$M_i = \frac{X_i+X_{i-1}+\cdots+X_{i-w+1}}{w}$
January	11	-10	-320	0	16.6	17.9
February	8	-13	-333	0	15.5	17.8
March	15	-6	-339	0	14.0	17.7
April	20	-1	-340	0	14.2	17.8
May	9	-12	-352	0	15.4	17.7
June	12	-9	-361	0	14.1	17.6
July	9	-12	-373	0	13.7	17.5
August	16	-5	-378	0	12.7	17.5
September	14	-7	-385	0	13.4	17.5
October	19	-2	-387	0	13.5	17.5
November	16	-5	-392	0	14.6	17.5
December	26	5	-387	0	14.9	17.6

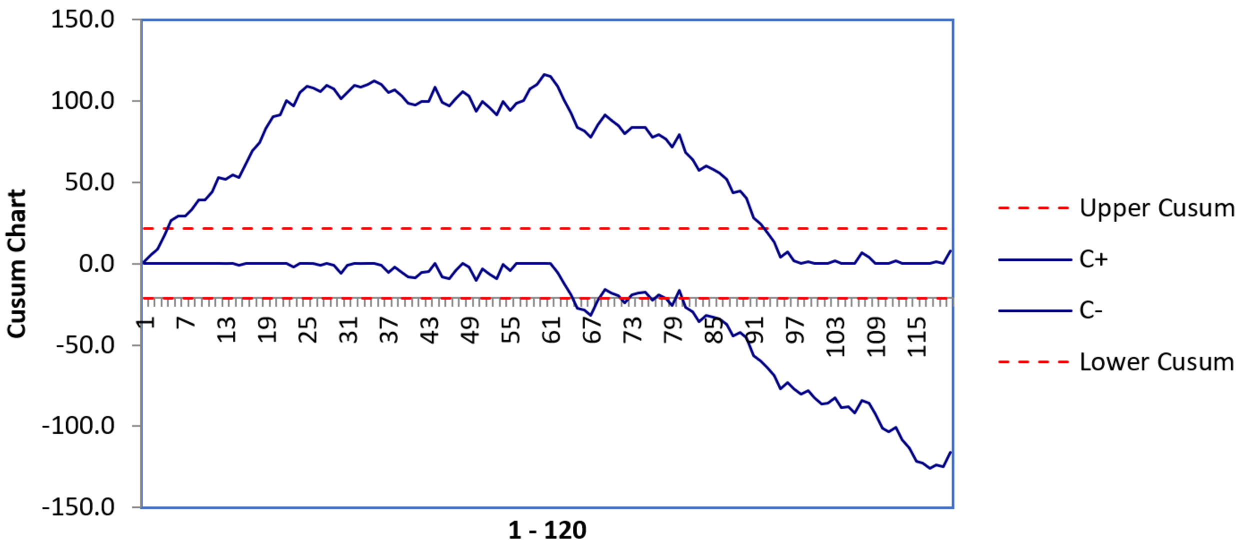

Figure 1.
Graphical representation of the CUSUM chart on fatalities of roadway accidents over the period 2015-2024.

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3.2. *Intervention of Analysis Performed by Exponentially Weighted Moving Average*

"The starting value of EWMA is $Z_0 = \mu_0 = 17$, and Z is the exponential weighted moving average of the value. In this study, we use w=0.2. The other values of EWMA statistics are computed similarly using Equation (7) over a 120-month period and are presented in Table 2 — Table 11. Using Equation (8) and Equation (9), we computed $UCL = 22.4$ and $LCL = 12.8$, where L is the width of the control limit assumed as 3. From calculated values, the road accident fatalities were out of control in the 12th month, and later it was out of control from the 18th month to the 26th month". The points of change in the process are identified and located on the EWMA chart in Figure 2.

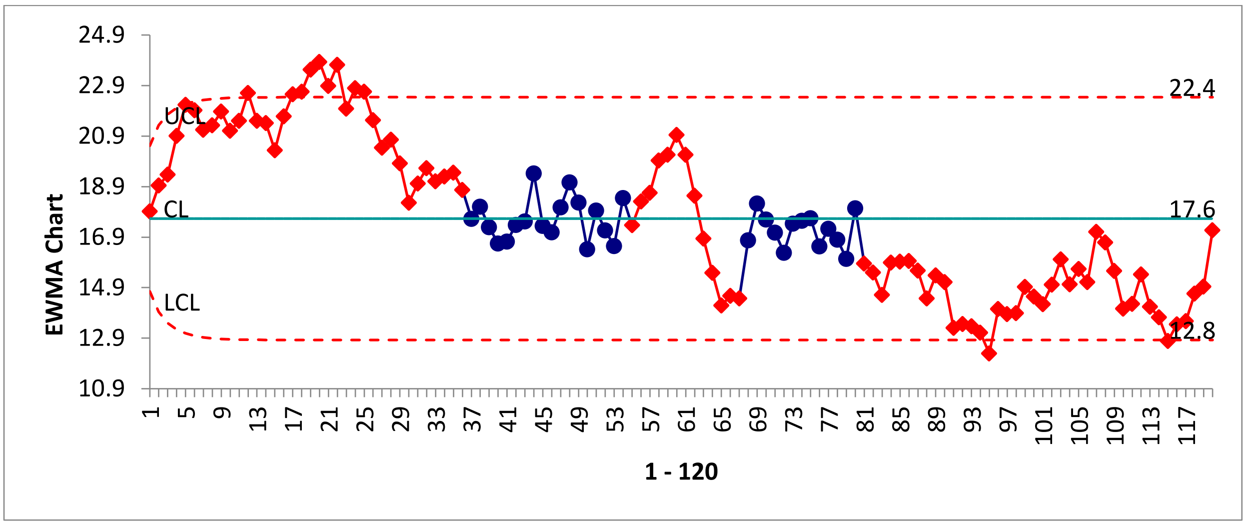

Figure 2.
Graphical representation of the EWMA chart on fatalities of roadway accidents over the period 2015-2024.

3.3. *Intervention of Analysis Performed by Moving Average*

"The values of Moving Average statistics are computed using Equation (10) over a 120 months period and are presented in Table 2 — Table 11. Using Equation (11) and Equation (12), we computed $UCL = 19.7$ and $LCL = 15.5$. Road accident fatalities, from calculated values, were out of control from the 4th month to the 6th month in the 12th month, later it was out of control from the 19th month to the 20th month, and in the 22th and 24th months." The points of change in the process are identified and located on the Moving Average chart in Figure 3.

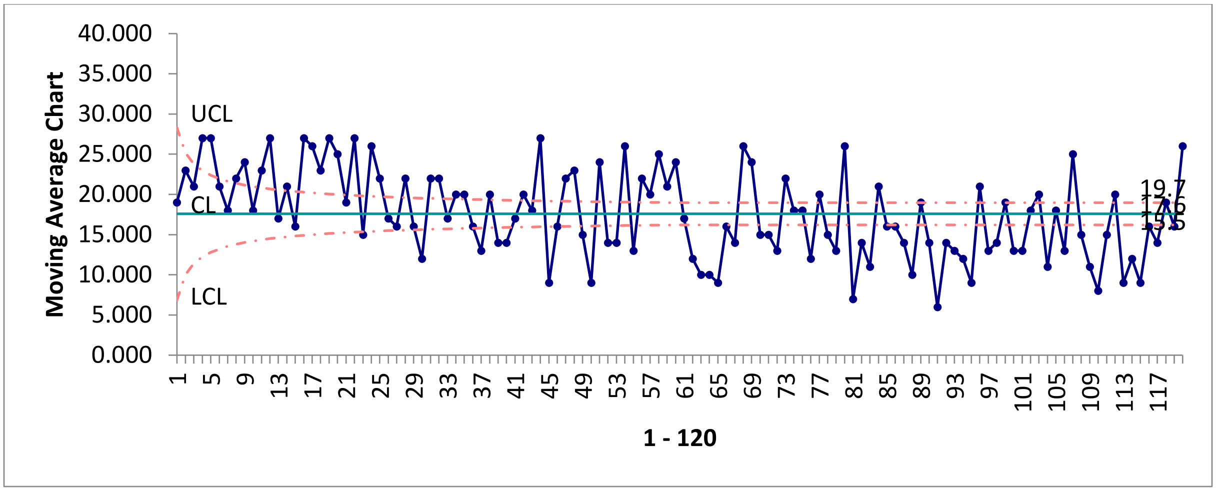

Figure3.
Graphical representation of the Moving Average chart on fatalities of roadway accidents over the period 2015-2024.

4. Discussion

Time-weighted statistical techniques, including Cumulative Sum (CUSUM), Exponentially Weighted Moving Average (EWMA), and Moving Average, are highly effective in detecting small process changes, particularly shifts in the mean of 1.5 sigma, as applied in this study. These techniques are widely recognized for their ability to identify subtle variations that may not be immediately apparent in conventional statistical analyses. Over the 120-month study period, the results indicate that among the three techniques, the Moving Average method provides the fastest response in detecting shifts in roadway accident fatalities. The computed values of roadway accident fatalities, as presented in Tables 2 to 11, revealed distinct differences in the detection times of each control chart method. The Moving Average chart signaled the first deviation at the 4th observation point, followed by the EWMA chart at the 12th point, and the CUSUM chart at the 18th point. This demonstrates that the Moving Average method is the most responsive in identifying small yet significant changes in the dataset. The earlier detection of shifts suggests that the Moving Average technique could be a more effective choice for monitoring sudden variations in accident fatality trends. Given its faster response time, the Moving Average control chart may be particularly advantageous for real-time traffic safety monitoring, where early detection of changes can enable authorities to implement timely interventions. The ability to detect shifts quickly is essential in developing proactive road safety policies, adjusting enforcement strategies, and mitigating accident risks. While EWMA and CUSUM techniques remain valuable for their ability to track long-term trends and cumulative variations, the Moving Average method's superior speed in signaling shifts makes it more suitable for datasets requiring immediate attention. Our findings suggest that control chart selection should be tailored to the specific objectives of traffic safety monitoring. If the goal is early intervention and rapid response, the Moving Average technique is the preferred option. However, for a more comprehensive analysis of long-term trends, integrating EWMA and CUSUM methods could provide additional insights into accident patterns and intervention effectiveness. Future studies may explore the combined use of multiple control charts to optimize roadway accident monitoring and enhance predictive accuracy.

5. Conclusion

Worldwide, road accidents are one of the leading causes of fatalities, affecting individuals of all ages, depriving them of their futures and dreams [53]. In this study, Cumulative Sum (CUSUM), Exponentially Weighted Moving Average (EWMA), and Moving Average statistical techniques—commonly used in quality control—were applied to detect sustained changes in roadway accident fatality trends over a 120-month period. This approach allowed for a thorough intervention and trend analysis, evaluating the impact of traffic safety measures over time. The comparative analysis of the three designed control charts demonstrated that all techniques were effective in detecting minor shifts from the mean. However, the Moving Average technique proved to be the most responsive, triggering alerts at a faster rate than the others. Additionally, all three methods successfully identified key points of change in the process, making them valuable tools for monitoring fatality trends. Among the control charts assessed, the Moving Average control chart emerged as the most efficient in detecting small process variations. Research suggests that it offers a more straightforward implementation compared to CUSUM and EWMA charts, while also being superior to the Shewhart chart in capturing subtle shifts in process behavior [48]. These findings provide a diagnostic framework for reducing roadway accident fatalities in Albania, contributing to enhanced monitoring and safety management strategies.

Furthermore, our results hold significant value for transportation authorities and public safety policymakers, offering insights that can guide the formulation of effective safety policies. The results highlight the importance of using data-driven decision-making to achieve long-term traffic safety improvements. Future research could explore the integration of multiple advanced control chart techniques to enhance detection accuracy and optimize intervention strategies for accident prevention.

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Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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