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Analyzing the Relationship between Sunset and Sunrise Times and Traffic Accident Rates

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Abstract: Sunshine glare during sunrise and sunset may contribute to a higher occurrence of traffic accidents, highlighting the need for preventive measures to enhance road safety. This study aims to analyze the relationship between sunrise and sunset times and road accident frequency and to assess the statistical significance of this relationship. The analysis is based on data from the Czech national road accident register, covering the period from October 2022 to October 2023, with over 90,000 accidents recorded. A paired t-test was conducted to compare accident frequencies during periods of sunlight exposure, and correlation coefficients were calculated to determine the relationship between accident frequency and sunset/sunrise times. The findings reveal a statistically significant increase in traffic accidents during sunrise and sunset periods, although the correlation between these times and accident frequency is weak but statistically significant. A key limitation of the study is its exclusive focus on sunrise and sunset times, without accounting for other potentially influential variables. Based on these results, practical recommendations are proposed, including enhancements to road infrastructure and adjustments to traffic schedules during high-risk time windows to reduce accident rates.

Keywords: Traffic accidents, driver glare, lighting conditions, accident risk factors, road traffic safety

1. Introduction

Traffic accidents significantly impact human lives and property, causing millions of injuries each year [1,2]. Moreover, they can result in serious lifelong mental health problems [3], thereby becoming a long-term issue [4]. Effective road safety management requires a thorough understanding of the nature of such accidents and the contributing factors [5]. Similarly, reducing the number of traffic accidents necessitates accurate prediction methods [6]. However, accurate traffic accident prediction presents several challenges, including data imbalance. Moreover, the majority of existing methods for predicting traffic accidents fail to consider the dynamic spatial and temporal correlations between incidents, which compromises predictive accuracy [7,8]. Traffic accidents typically result from a combination of various elements interacting and evolving over time, influencing the complexity and accuracy of predictions. This dynamic nature requires a comprehensive analysis [1,9]. Therefore, an effective accident prediction model must be based on accurate data reflecting a wide range of influencing factors [10]. As mentioned above, often arise due to a variety of factors, most commonly including weather conditions, road infrastructure, and human factor. These factors are often interrelated and may interact in various ways [11]. This observation is supported by [12], who also highlighted the failure to comply with traffic regulations as a major contributor. Assessing the factors contributing to traffic accidents is thus of essential both for predicting incidents and developing effective programs aimed at reducing traffic accident rates [13].

Human errors, such as the behaviors of cyclists and motorcyclists, along with adverse weather conditions and limited visibility, have been identified through statistical analysis as the most frequent causes of traffic accidents [14]. Insufficient visibility significantly impacts road safety and contributes to the occurrence of traffic accidents. However, traditional methods of monitoring visibility are increasingly inadequate in meeting current demands [15]. Additionally, driver glare, including the improper use of high beams during nighttime, is also recognized as a significant factor contributing to accidents [16]. Studies confirm that glare can impair visual performance and induce discomfort, thereby increasing the likelihood of traffic accidents for drivers [17]. Authors [18] analyzed 99 fatal traffic accidents in Slovakia caused by drivers with less than five years of experience. Although no direct correlation was found between specific driving schools and accident rates, the study identified systematic deficiencies in the quality of driver training, supported by official inspections. The findings underscore the importance of high-quality training and supervision as key components of road safety in the Central European context.

This paper seeks to assess the influence of sunrise and sunset times on the frequency of traffic accidents and to determine their statistical significance.

The answer to RQ1 will reveal whether the frequency of traffic accidents occurring at sunset and sunrise times differ significantly from the number of traffic accidents occurring at other times of the day. This question is key to the identification of times associated with higher traffic accident risk and may contribute to designing measures to improve road safety.

RQ1: Is there a statistically significant difference in the number of traffic accidents occurring at the times of sunset and sunrise compared to other times of the day?

Understanding the impact of sunrise and sunset times on traffic accident frequency is crucial for analyzing road safety dynamics. The answers to the second and third research questions will inform the development of more effective strategies to prevent traffic accidents and optimize transport policies. Determining the influence of sunrise and sunset times can aid in minimizing traffic accident risks and enhancing overall road safety.

RQ2: Does the sunrise time influence the number of traffic accidents during the day?

RQ3: Does the sunset time influence the number of traffic accidents during the day?

Most studies on traffic accident prediction rely on statistical methods with individual deep learning models without considering the visual influence of the urban environment on drivers and their behavior. Many of these models, however, suffer from the problem of zero inflation, which leads to low prediction performance. In [19], a model for assessing urban traffic accident risk was developed, integrating spatial and visual factors that influence driver behavior. Due to the limitations of traditional methods, [6] applied deep learning methods for traffic accident prediction. Initially, a knowledge graph was utilized to examine the relationships among various traffic accident factors, combined with a continuous wavelet transforms. These approaches resulted in a prediction accuracy of 99.32%. In [20], deep learning technology was used to estimate traffic accident severity and address the the shortcomings of previous research. The proposed system consisted of three steps - data cleaning, preprocessing and experimentation. The findings indicated that the method delivered superior accuracy and outperformed other systems. In [21], the research focused on forecasting the number of traffic accidents by considering the weight and interdependence of variables through grey correlation analysis to assess the impact of each factor. Subsequently, the prediction process was modeled using a multivariate grey model.

The research by [22], investigates the relationship between fatal road accidents and their contributing risk factors. A descriptive analysis was utilized to characterize individuals involved in road accidents, while a binary logistic regression approach was employed to identify key factors affecting fatal road crashes. The results revealed that speeding, drunk driving, fatigue, and pedestrian behavior significantly increased the likelihood of a fatal crash. In [23], various machine learning methods, including supervised and unsupervised learning, were applied. The authors concluded that, contrary to expectations, factors like weather, season, and day of the week had no significant impact on traffic accident severity.

The study by [24] investigated factors contributing to traffic accidents applying a topological approach to analyze intricate network structures. Dimensionality reduction techniques were employed to simplify the analytical metrics, which were then classified using four machine learning techniques to assess accident severity. The traffic accident data were categorized into three distinct groups: time-related factors, environmental factors, and traffic control measures. The findings indicate that traffic control factors exert the strongest influence on traffic accident occurrence. [25] focus on identifying the key factors influencing road incidents while minimizing the likelihood of such accidents using improved artificial neural network methods. The authors concluded that factors such as road conditions, weather, road surface, and time significantly influence the occurrence of traffic accidents, and their quantification and minimization of their redundancy is thus essential. The connection between various factors and accident severity was assessed through a proposed neural network prediction model with multiple inputs and multiple outputs. The validity of the method was verified using data from over 10,000 traffic accidents and demonstrated higher accuracy and stability than traditional approaches. The research in [26] examines the relationship between the number of accidents and lighting as a factor in their occurrence. Similarly, causes of accidents are also addressed by [27], who investigate driver response time within a simulation environment, with a focus on young drivers (under the age of 26) and analyzed the effect of gender, driving experience and alcohol consumption on reaction time. The applied methods included a one-sample t-test, paired t-test, independent samples t-test, and correlation analysis. The results showed a significant effect of alcohol and other factors on driver reaction times.

Research [28] focuses on accurately predicting traffic accident risks using a proposed MVMT-STN model, which estimates accident risks at both detailed and broader levels. This model leverages multi-task learning by combining a channel-specific convolutional neural network (CNN) combined with a multi-view graph convolutional network (GCN) to model spatial and contextual relationships. In earlier studies, [29] examined the relationship between road surface skid resistance and highway crash occurrence. Correlation analysis was used to analyze the influence of three factors, namely road geometry, climatic factors, and surface skid resistance. The results confirmed a correlation between these variables and traffic accident frequency. [30] focus on the analysis and construction of a knowledge graph or road incidents using case-specific data that included dynamic and static factors such as human behavior, vehicles, road conditions, and the environment. The resulting knowledge graph facilitates the visual analysis of traffic accidents through perspectives such as accident profiling, classification, statistics, and correlation pathways. This method integrates machine and human cognitive process, thereby enhancing the interpretability of complex data.

2. Data and Methods

The research includes a detailed examination of the potential relationship between road traffic accident frequency and sunset and sunrise times. Daily data were collected from 1 January 2023 to 31 December 2023 [31]. Based on observations of solar elevation during the day, time intervals during which the sun can significantly impair drivers' visibility on the road were identified. Specifically, these intervals are defined as 2 hours before and 2 hours after both sunrise and sunset. To ensure a fair comparison, accident counts occurring during the remaining 20 hours of the day were normalized by calculating the average per 4-hour period, corresponding to the duration of the sunrise and sunset windows.

Data on the frequency of road accidents were obtained from the website [32]. From this dataset, the specific times and dates of individual accidents were extracted. The selected study period spans from 1 November 2022 to 9 December 2023, during which over 90,000 accidents were analyzed. This dataset provides a robust basis for statistical analysis and allows for the identification of patterns and trends in the number of accidents in relation to sunrise time.

As a first step, the annual frequency of traffic incidents within the study period was assessed using a line graph. Next, the number of traffic accidents occurring during sunrise or sunset times was examined. For this purpose, two hypotheses are formulated. Given the sample size and the nature of the data, a paired sample t-test was selected to test each hypothesis.

The difference between each pair of observations is calculated as follows:

$$D_i = X_i - Y_i, \quad [-] \tag{1}$$

where: X_i and Y_i represent the individual data points in each pair [-].

The mean of these differences is determined using the following formula:

$$\bar{D} = \frac{1}{n}\sum_{i=1}^{n} D_i, \quad [-] \tag{2}$$

where: $\bar{D}$ is the mean of the differences [-], n is the total number of paired observations [-], and $\sum_{i=1}^{n} D_i$ denotes the sum of all individual differences [-].

Standard deviation of the differences is calculated as follows:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(D_i - \bar{D})^2}{n-1}}, \quad [-] \tag{3}$$

where: SD is the standard deviation of the differences [-] $(D_i - \bar{D})^2$ represents the squared deviation of each value from the mean difference [-], n is the total number of pairs [-], and $n-1$ is used to correct for sample bias (Bessel's correction).

For calculating the t-statistic, the following formula is used:

$$t = \frac{\bar{D}}{SD\sqrt{n}}, \quad [-] \tag{4}$$

where: $\bar{D}$ is the mean difference [-], SD is the standard deviation of the differences [-], and $\sqrt{n}$ adjusts for sample size in estimating the standard error of the mean [-].

3. Results

The following chapter focuses on the analysis of the effect of sunrise and sunset times on the frequency of traffic accidents.

The first section provides a timeline of recorded traffic accidents for the years 2022 and 2023. Figure 1 comprises three separate graphs illustrating (1) the number of accidents occurring within the four-hour window surrounding sunrise, (2) the number of accidents during the remainder of the day, and (3) the average number of accidents per four-hour interval.

Figure 2 provides a direct comparison between the number of accidents during the sunrise window and the average number of accidents during the rest of the day (adjusted to the equivalent four-hour period).

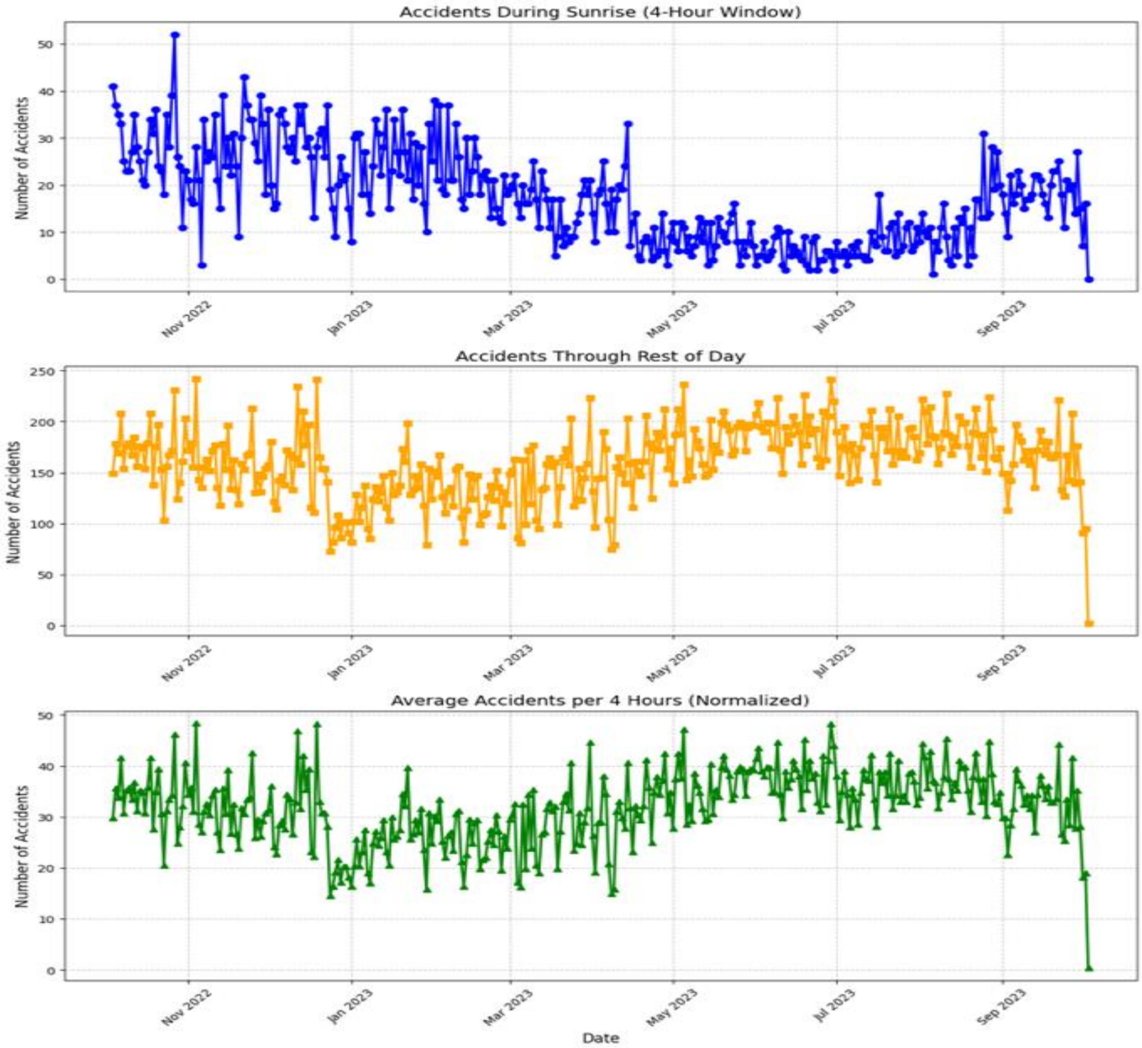


Fig. 1 Daily Traffic Accidents During Sunrise and the Rest of the Day Accidents Rate. Source: authors

Hypothesis on the influence of sunrise time on the number of accidents:

Null Hypothesis (H_0): Sunrise time does not have a statistically significant effect on the frequency of traffic accidents.

Alternative Hypothesis(H_1): sunrise time has a statistically significant effect on the frequency of traffic accidents, leading to either an increase or decrease in accident frequency depending on the timing of sunrise.

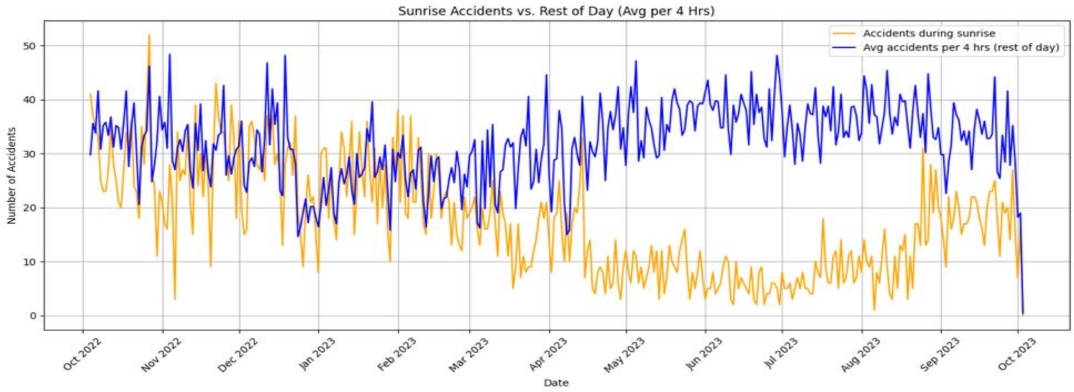


Fig. 2 Sunrise Accidents vs. Rest of the Day Accidents Rate. Source: authors

The results of the pairwise comparison reveal a statistically significant difference in the average number of accidents occurring between the sunrise period and the rest of the day (see Table 1). Specifically, the four-hour period around sunrise recorded an average of 17.33 accidents, whereas the average for the remainder of the day was 31.90. This disparity suggests that accident occurrence is influenced by the time of day. Furthermore, the variability in accident counts was greater during the sunrise (standard deviation = 9.98) compared to the remainder of the day (standard deviation = 7.09), possibly due to changing light conditions. These values serve as the basis for a paired t-test to assess the statistical significance of the observed difference.

Table 1 Paired Sample Statistics. Source: authors

		Mean	Std. Deviation	Std. Error Mean
Pair 1	Number of Accident (Sunrise)	17.33	9.98	0.52
	Number of Accidents (Rest of the day)	31.9	7.09	0.37

As shown in Table 2, the analysis reveals a weak negative correlation between the number of accidents occurring during sunrise and during the rest of the day ($r = -0.108$, $p = 0.038$). This indicates a statistically significant but very weak inverse relationship, where a slight decrease in sunrise accidents may correspond to a slight increase during other times of the day and vice versa. Despite the limited strength of the correlation, the findings support further investigation into how time of day affects accident rates, especially regarding light and traffic conditions.

Table 2 Paired Samples Correlations. Source: authors

		Corr	Sig.
Pair 1	Number of Accidents (Sunrise) & Accidents (Rest of the day)	-108	0.038

The results of the paired t-test (see Table 3) indicate a statistically significant difference in the number of accidents between the sunrise period and the rest of the day. The mean difference is -142.186 accidents, with a standard deviation of 37.852 and a standard error of the mean of 1.981. The confidence interval (95%) for this difference ranges from -146.083 to -138.290, not including zero, which leads to the rejection of the null hypothesis. The test result, $t(364) = -71.76$ and $p < 0.001$ confirms that the difference is highly statistically significant. These findings provide robust evidence in support of the alternative hypothesis, indicating that sunrise time has a significant effect on the frequency of traffic accidents.

Table 3 Paired Samples Test. Source: authors

		Paired Differences					t	df
		Mean	Std. Deviation	Std. Error Mean	95% CI (Diff)			
					Lower	Upper		
P1	Number of Accidents (Sunrise) & (Rest of the day)	-142.186	37.852	1.981	-146.083	-138.29	-71.76	364

As shown in Table 4, the effect size estimates confirm the significant difference in the number of traffic accidents between the sunrise period and the rest of the day. The estimate of Cohen's d was -3.756, with a 95% confidence interval ranging from -146.083 and -138.290. Hedges' g, which adjusts for potential bias in smaller samples, yielded a similar value of -3.749. Both metrics are derived from the standard deviation of the differences between paired samples and clearly indicate that the difference between the time periods analyzed is statistically significant. These results further support the conclusion that the sunrise period has a major impact on the occurrence of traffic accidents.

Table 4 Paired Samples Effect Sizes. Source: authors

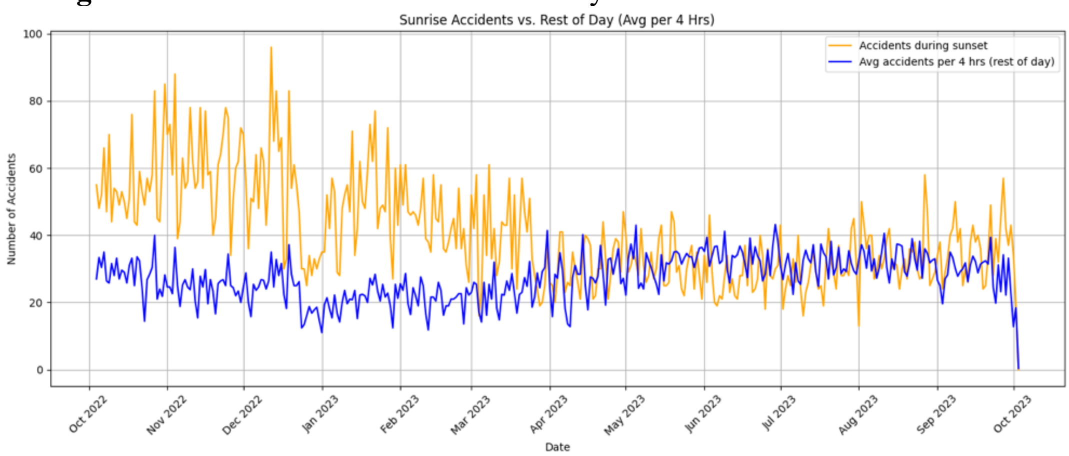
			Standardizer	Point Estimate	95% CI	
					Lower	Upper
Pair 1	Number of Accidents (Sunrise)	Cohen's d	37.852	-3.756	-146.083	-138.29
	Number of Accidents (Rest of the day)	Hedges' correction	37.852	-3.749	-146.083	-138.29

Hypothesis for Sunset Influence on Accidents:

Null Hypothesis (H_0): The time of sunset does not have a significant impact on the number of accidents.

Alternative Hypothesis (H_1): The time of sunset significantly impacts the number of accidents, resulting in either an increase or decrease in accident frequency in relation to the time of sunset.

Fig. 3 Sunset Accidents vs. Rest of the Day Accidents Rate. Source: authors



The statistics presented in Table 5 show significant differences in the average number of traffic accidents occurring during the sunset period compared to the remaining hours of the day. During the four-hour period around sunset, an average of 40.7 accidents was recorded, while the average number of accidents during pre- and post-sunset periods was only 27.33 crashes. This finding indicates a higher incidence of accidents coinciding with sunset hours. Furthermore, the standard deviation during the sunset period (15.12) exceeds that of the other periods of the day (6.53), suggesting greater variability in traffic conditions and situations during the evening hours. These results are further illustrated in Figure 3.

Table 5 Paired Samples Statistics. Source: authors

		Mean	Std. Deviation	Std. Error Mean
Pair 1	Number of Accidents (Sunset)	40.7	15.12	0.79
	Accidents (Rest of the day)	27.33	6.53	0.34

As shown in Table 6, there is a very weak negative correlation ($r = -0.099$, $p = 0.060$) between the number of accidents during the sunset period and in the pre- and post-sunset time periods. This correlation is not statistically significant ($p > 0.05$). Thus, the findings suggest that there is no strong systematic relationship between the two time periods, indicating that the occurrence of accidents during sunset cannot be reliably predicted based on accident rates in the surrounding hours. This finding highlights the potential influence of specific factors linked directly to the time of sunset.

Table 6 Paired Samples Correlations. Source: authors

		Correlation	Sig.
Pair 1	Number of Accidents (Sunset) & Accidents (Rest of the day)	-0.099	0.06

The results of the paired t-test (Table 7) show a statistically significant difference in the number of accidents between the sunset period and the periods before and after sunset. The mean difference was 13.371 accidents, with a standard deviation of 17.051 and a standard error of the mean of 0.894. The 95% confidence interval for the mean difference ranged from 11.614 to 15.129, excluding zero and thereby supporting the rejection of the null hypothesis. The t-test yielded $t(364) = 14.96$, with a p-value < 0.001, confirming the statistical significance of the observed difference. These results provide strong evidence in favor of the alternative hypothesis.

Table 7 Paired Samples t-test. Source: authors

		Paired Differences					t	df
		Mean	Std. Dev.	Std. Error Mean	95% CI (Diff) Lower	95% CI (Diff) Upper		
Pair 1	Number of Accidents (Sunset) & Accidents (Rest of the day)	13.371	17.051	0.894	11.614	15.129	14.96	364

As shown in Table 8, the resulting effect sizes indicate a moderate to strong difference in accident frequency between the sunset period and the surrounding time intervals. Cohen's d value was calculated at 0.784, while Hedges' g, which applies a sample size correction, wa 0.783. Both values are based on the standard deviation of the differences between paired observations (17.051) and show that sunset has a significant effect on accident rates. Although the effect is not as pronounced as that observed for sunrise, it remains statistically significant.

Table 8 Paired Samples Effect Sizes. Source: authors

			Standardizer[a]	Point Estimate	95% CI Lower	95% CI Upper
Pair 1	Number of Accidents (Sunset) - Accidents (Rest of the day)	Cohen's d	17.051	0.784	11.614	15.129
		Hedges' corr.	17.051	0.783	11.614	15.129

4. Discussion

RQ1: Is there a statistically significant difference in the number of accidents occurring at sunset and sunrise compared to other times of the day?

The analysis confirmed that both sunrise and sunset periods significantly influence the frequency of traffic accidents. On average, 17.33 accidents occur during the sunrise period, compared to 31.90 accidents throughout the rest of the day. For sunset, the average is 40.7 compared to 27.33 during other hours. Although the intervals are shorter, paired t-tests confirmed statistically significant differences. These findings are consistent with previous research [33] and align with broader regional findings on traffic safety patterns in Central Europe [34]. The results suggest that these high-risk periods should be considered in traffic prevention strategies, e.g., through targeted education for less experienced drivers [5,18].

RQ2: Does the sunrise time influence the number of traffic accidents during the day??

The results indicate that sunrise time has a statistically significant effect on accident rates. A paired t-test showed a substantial difference ($t(364) = -71.76$; $p < 0.001$) with a large effect size (Cohen's $d = -3.756$). Furthermore, a weak negative correlation ($r = -0.108$) suggests that this is not simply a reflection of general daily trends. These findings are in line with previous research [25] and may partially explain the seasonal variations in accident rates, as described, for example, in [2].

RQ3: Does the sunset time influence the number of traffic accidents during the day?

Similarly, the sunset period also showed a statistically significant effect on the number of accidents ($t(364) = 14.96$; $p < 0.001$), with a moderate effect size (Cohen's $d = 0.784$). The correlation between accident counts during the sunset period and surrounding time intervals was very weak and not statistically significant ($r = -0.099$; $p = 0.060$). In addition to reduced visibility, other contributing factors such as driver fatigue or alcohol consumption may also play a role [22].

5. Conclusion

The findings demonstrate that both sunrise and sunset periods have a significant impact on the total number of traffic accidents during the day. Despite their short duration, these time windows showed a statistically significant differences, with a particularly strong effect observed at sunrise and a moderate effect at sunset. The present research focused exclusively on statistical differences in accident frequency and did not include a detailed analysis of the underlying causes or specific circumstances. Moreover, the analysis was based on data from a single year, which may limit the generalizability over a longer time horizon. Future research should examine how light-related accident risks interact with factors such as weather conditions, road types, and driver demographics. Incorporating behavioral and vehicle data could further improve risk prediction.

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