PREDICTING ACCIDENT RATE IN CR AND EU

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Abstract: Predicting accident rates is vital for preventing road accidents and effectively planning safety measures. Our study focuses on forecasting the movement of the accident rates in the Czech Republic and EU countries. Using ETS statistical models for data analysis, our goal is to indicate underlying trends in the volume and gravity of road accidents. Our research tackles the main issues that could affect future accident rates. Although our results show a likely downward trend in road crashes in the Czech Republic and the EU in the following years, the rate of road accident decline may vary throughout the countries. The research findings help impose practical safety measures and strategies adapted to local conditions.

Keywords: Road accident rates, Prediction, The Czech Republic, The European Union, ETS, Safety measures

1 Introduction

Road accidents happen because of heavy traffic, taking their toll on human lives, social sentiments and economic stability [1]. Countries and global organizations pursue strategies for diminishing the volume of road accidents and their negative impacts, as preventing road deaths is the primary goal when implementing safety measures. Strategies like using modern technologies, providing decent education and assuming ultimate responsibility in the transport area led to a decline in fatalities [2].

Accident rates depend on many factors, including human failure, technical condition of the vehicle and roadway [3]. State organizations may profoundly affect these areas; state technical inspections and legislation govern the vehicle technical condition, and infrastructure investments supervise roadway conditions. Human error is proportional to the drivers' education, knowledge and toughening of the rules for driving offences [4]. Interventions like regulations on the technical conditions of the vehicle may immediately decrease accident rates, while drivers' education requires a long time to be effective. For example, motorcyclists' risky behavior, one of the critical factors, can be controlled by long-term educational campaigns [5].

Although many countries have seen a decrease in road accident rates [6], we cannot predict if the European Union will achieve its ambitious goal within its 'Vision Zero' strategy, aiming to halve the number of fatalities through 2030 and zero the death toll out through 2050 [7]. This decade has focused on educating drivers about road safety, monitoring vehicle construction safety and healthcare development [8].

Traffic density, a significant contributor to road accidents, increases with better economic conditions, allowing low-income classes to buy their own vehicles. The COVID-19 pandemic saw a sharp decline in road accidents throughout the countries [9], caused by the restriction of movement and decreased traffic density. This phenomenon shows that reducing road traffic, e.g. by using public transport or car sharing, would effectively cut long-term road accident rates.

The findings suggest that the factors influencing accident rates are interwoven, requiring unorthodox methods in terms of technologies, education and infrastructure [10]. Effective prevention involves taking precautionary steps on the national and global scale.

The study aims to predict accident rates in the Czech Republic and the EU, exploring their frequency within the following years. We formulated the following research questions:

RQ1 involves forecasting the accident rates in the Czech Republic based on the historical data from 2011 to 2024. It aims to predict and analyze underlying trends and seasonal fluctuations in the accident rates influencing the development of transport policies and preventative measures.

RQ1: What will the accident rates be in the Czech Republic withing the following 18 months?

RQ2 involves forecasting the accident rates in the EU within the following two years (2024 - 2026), using historical data from 1999 to 2023.

RQ2: What will the accident rates be in the EU within the following five years?

2 Literary research

[11] analyzed road casualties in time using year-over-year variance, revealing a slightly decreasing trend in road deaths. [12] explored 11-year trends in accident rates using descriptive statistics, disclosing a continuous, yet too slow to meet the goals, decline in road casualties. [13] examined road accidents outside rush-hour traffic, where road collisions indicated a growing tendency, contrasted to a downward trend in the rates during rush hour. [14] supports the claim of lowering road death rates by an ETS road accident overview, revealing a falling number of road accidents and casualties over the monitored period.

Reliable prediction requires an effective method of data processing. [15] used an LSTM-GBRT model implemented into road accident rate data, finding higher fit accuracy than regression models using neural networks. The model requires normality, structure and more data to be reliable. [16] analyzed the data fit of road accident rates on an ETS model. The authors found that the model is ideal for predicting from historical data, revealing a slight increase in road casualties in India. Not requiring linearity or normal distribution, the model can handle less data. [17] conducted similar research using an ARIMA model fitted to handle extensive historical data. The predicted values mimicked the increasing road accident rates in India. [8] applied seasonality to the ARIMA, achieving a good data fit only during seasonal fluctuations. [18] explored an RF model implemented into historical data to predict the future gravity of road accidents. The authors revealed a very accurate model fit, successfully identifying the driver's experience, lighting conditions, the driver's age, the day of the accident, and vehicle age as distinguishing factors between slight, critical and fatal injuries.

[19] explored factors, prediction algorithms and explanatory methods of predicting the risks of road accidents based on driver behavior using a systematic literature overview. The authors revealed that speed and acceleration are the most frequent determinants. A different factor influencing the results of prediction methods may be the COVID-19 pandemic, cutting road accident rates because of tight movement restrictions [20]. [21] used regression models, neural networks and ARIMA for modelling road accidents, injuries and deaths, revealing a dramatic decline in road accident rates by 35%, injuries by 50% and deaths by 37% during the pandemic. [22] applied an ARIMA model, Holt-Winters, Bayesian structural time series and generalized additive models, finding that the COVID-19 pandemic had decreased road injury tolls that prevailed until post-pandemic periods. The severity of traffic accidents also affects the wearing of protective equipment when riding two-track vehicles, which was addressed by [23] who investigated the safety habits of users of shared e-scooters, where the results found zero protection for users of this mode of transport.

[24] used machine learning and field research to identify hot spots (places with high accident rates), unveiling that street furniture and geometric elements significantly contribute to road safety. [25] applied Regression Analysis, Correlation Analysis, and the Ramsey RESET test to data about dangerous situations,

revealing that the data helps identify the hotspots. [26] evaluated motorway traffic using a time series-based ARIMA model, disclosing an unsteady increase in safety. Although low accident rates substantially contribute to fulfilling ‘Vision ZERO,’ they are not enough to achieve a zero death rate, which largely depends on motor vehicle safety. [27] tackled the issue using content analysis and neural networks, uncovering a steady increase in motor vehicle safety. Neural networks, such as LSTM (Long Short-Term Memory), play a crucial role in prediction approach [28].

[29] explored speed as another threat to passenger safety using a SARIMAX model. Although the authors found an inverse relationship between speed and accident rates, speeding and fatalities are positively correlated. On the other hand, some factors do not give us an obvious clue whether they contribute to accident rates and road safety. [30] analyzed how weather influences road accident rates using a two-dimensional model of a discreet time series BINAR (1), revealing ambiguous results. What significantly increases road accident rates is alcohol consumption. [31] explored the impacts of intoxicated driving on health during road crashes. Using the Shapiro-Wilk test and descriptive analysis, the authors found that drunk-driving accidents extend the hospital stay and increase the risk of disability.

Understanding the factors influencing accident rates and exploring the accuracy of previous predictions may be imperative for conducting research and imposing measures for reducing road crashes.

Based on previous data analyses, we use the Shapiro-Wilk test and Ramsey RESET test to understand the data structures, including ERROR, Trend and Seasonality model (ETS model) for making analysis and predictions.

3 Data and methods

In this section, the results of the analysis of this research will be published and discussed.

3.1 Data

The first research question involves the data from the Czech public database containing information about accidents [32], filtering the data on monthly accident rates from January 2011 to September 2024. The data from March 2020 through December 2021, distorted by the COVID-19 pandemic, are ruled out of the calculation using a dummy variable to avoid misrepresentation.

The second research question draws on the Eurostat database [33] using a data pack (Road accidents by NUTS 3 region) containing total road accidents in the EU states from 1999 through 2023. As in the previous case, a dummy variable rules out the variables from 2020 and 2021 to avoid information bias caused by COVID-19.

3.2 Methods

An accurate prediction within the first research question (RQ1) depends on taking reasonable steps and statistical tests that help understand the data structure. When this is fulfilled, we can choose an effective method for predicting future road accident rates in the Czech Republic.

The first step involves normality tests for the data, which is imperative for selecting the convenient method. When normality is proven, we choose ARIMA to forecast road accident rates when the data is linear. Ramsey The RESET test confirms or rejects data linearity, assessing whether the model specifications are correct and detecting non-linearity. Its results can be interpreted by the resulting p-value. A p-value higher than 0.05 confirms, whereas the opposite rejects it.

Formula according to [34]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \gamma_1 \hat{Y}^2 + \gamma_2 \hat{Y}^3 + \epsilon$$

Where:

- Y is dependent variable.
- $X_1, X_2, \ldots, X_k$ are independent variables
- $\hat{Y}$ are the predicted values of the original model.
- $\hat{Y}^2$ a $\hat{Y}^3$ are quadratic and cubic values added into the model.
- ϵ is error

The Shapiro-Wilk test involves the second control examination, confirming or rejecting normal distribution. Symmetric (normal) distribution of the data is imperative for choosing the correct prediction model. When interpreting the results, a p-value higher than 0.05 confirms normality.

Formula according to [35]:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

Where:

- W is the Shapiro-Wilk test value
- $x_{(i)}$ are values in the ascending order
- $\bar{x}$ is the mean of the data values
- $a_{(i)}$ are pre-calculated weight coefficients dependent on the size of the sample
- n is the size of the sample

In the event of non-linear data distribution, we use ETS (Error-Trend-Seasonality) to smooth previous time series values, assuming future values based on exponentially decreasing weights of the prior values. The model is perfect for the time series based on trendiness and seasonality, where previous values are of less weight when estimating future trends.

Formula according to [36]:

$$Y_t = (l_{t-1} + b_{t-1}) \cdot s_{t-m} + \varepsilon_t$$

Where:

- Y_t is a time series value in time t
- l_t is an estimate of the level in time t
- b_t is an estimate of the trend in time t
- s_t is seasonality in time t
- m is the number of seasons in the year
- ε_t are residues in time t

4 Resutls

According to the research questions, we made visualized predictions in RStudio program.

4.2 RQ1 rusults

We use structured data analysis as a base for selecting comprehensive analysis of the prediction.

Figure No.1: Basic data structures for RQ1

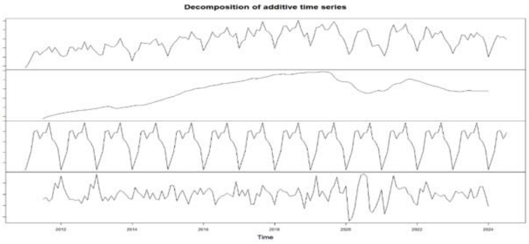
```
      Date                Accidents
 Min.   :2011-02-01   Min.   : 4800
 1st Qu.:2014-06-16   1st Qu.: 7045
 Median :2017-11-01   Median : 7974
 Mean   :2017-10-31   Mean   : 7833
 3rd Qu.:2021-03-16   3rd Qu.: 8646
 Max.   :2024-08-01   Max.   :10066
```

Source: author

The data spans the period from February 2011 through August 2024, reaching a median in November 2017. The accident rates range from 4800 to 10066, marking the average at 7833 and the median at 7974. The highest values appear in the last quartile, indicating a growing trend. The time series shows a steady accident rate development with a seasonality for potential analysis and prediction.

To better understand the data structure, we visualize the decomposition of additive time series, which is an effective method for decomposing time series into different components.

Figure No.2: Decomposition of additive time series



Source: author

The decomposition of the additive series suggests the trend, seasonality and random components. The trend grows until 2019, followed by a decline. Seasonality reveals regular annual fluctuations, indicating cyclical changes in yearlong accident rates, with lower numbers in winter months. Random components reflect unusual deviations beyond the explanations of the trend or seasonality.

The Shapiro-Wilk test will confirm or reject normal distribution of data.

Figure No.3: Results of the Shapiro-Wilk testu for RQ1

```
        Shapiro-Wilk normality test

data:  data$Accidents
W = 0.98814, p-value = 0.1853
```

Source: author

The Shapiro-Wilk test with a p-value higher than 0.05 and W close to 1 suggests no deviations from normal distribution, indicating normal distribution of data.

The final step involves the Ramsey RESET test applied to the basic linear model to check the residues.

Figure No.4: Results of the RESET test for VO1

```
        RESET test

data:  model
RESET = 41.943, df1 = 2, df2 = 158, p-value = 2.447e-15
```

Source: author

The results of the Ramsey RESET test show a low p-value (lower than 0.05), indicating data non-linearity, which makes the ARIMA model inefficient. We chose a non-linear ETS model.

As the non-linear ETS model effectively handles trendiness and seasonality, it makes accurate predictions despite non-linear relationships.

Table No.1: Results of ETS model for RQ1

Parameter	Value
Alpha	0.4968
Beta	1.00E-04
Gamma	1.00E-04
Phi	0.9799
Level (l)	6007.5675
Slope (b)	51.5918
Seasonality (s)	0.9612, 1.0012, 1.0161, 1.1183, 1.0549, 1.0489, 1.0216, 1.0642, 1.0601, 0.9406, 0.8873, 0.8256
Sigma (Error)	0.0508
AIC	2797.466
AICc	2802.216
BIC	2853.153
ME	-8.51241
RMSE	376.9489
MAE	269.2139
MPE	-0.2799843
MAPE	3.51011
MASE	0.5438518
ACF1	0.1412163

Source: author

Table 1 illustrates the results of the ETS model used to predict road accident rates. The key values involve the following smoothing parameters: Alpha (0.4968), Beta (1e-04), and Gamma (1e-04). The model reaches AIC values (2797.466), RMSE (376.9489) and MAPE (3.51011). seasonality changes between 0.9612 and 1.1183, indicating a very accurate data prediction.

Table No.2: Prediction of ETS model for RQ1

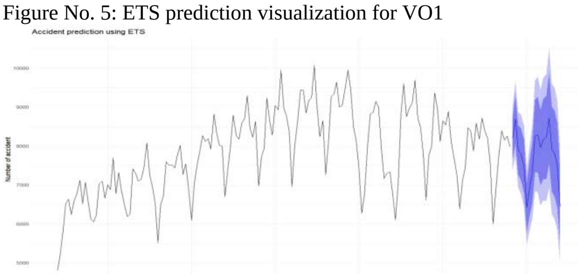
Month-Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Aug 2024	8198.182	7664.142	8732.222	7381.439	9014.925
Sep 2024	8692.992	8060.519	9325.464	7725.709	9660.275
Oct 2024	7900.448	7271.166	8529.730	6938.045	8862.851
Nov 2024	7786.350	7116.731	8455.970	6762.255	8810.445
Dec 2024	7476.168	6789.007	8163.328	6425.247	8527.088
Jan 2025	6423.211	5797.121	7049.301	5465.689	7380.733
Feb 2025	6904.140	6194.837	7613.442	5819.355	7988.924
Mar 2025	7320.622	6531.860	8109.383	6114.315	8526.928
Apr 2025	8252.482	7323.790	9181.175	6832.169	9672.795
May 2025	8285.804	7315.269	9256.339	6801.499	9770.109
Jun 2025	7955.379	6988.332	8922.425	6476.408	9434.349
Jul 2025	8169.682	7141.668	9197.697	6597.470	9741.894
Aug 2025	8217.768	7149.696	9285.840	6584.292	9851.243
Sep 2025	8713.338	7545.901	9880.774	6927.898	10498.778
Oct 2025	7918.563	6826.748	9010.379	6248.776	9588.351
Nov 2025	7803.841	6698.242	8909.441	6112.973	9494.710
Dec 2025	7492.621	6403.412	8581.829	5826.820	9158.422
Jan 2026	6437.060	5478.074	7396.045	4970.418	7903.702

Source: author

Table 2 depicts the prediction of road accident rates from August 2024 to January 2026, suggesting that road accident rates could oscillate between 8,000 and 8,700 cases, except for January, when they should move around 6,400 crashes. The Lo 80/95 and Hi 80/95 ranges provide confidence intervals, estimating the lowest number around 5,500 and the highest around 10,000 cases.

Figure 5 illustrates historical data on accident rates, highlighting the prediction in blue; light blue represents high confidence intervals (95%), and dark shade depicts low confidence intervals (80%).

Figure No. 5: ETS prediction visualization for VO1



Source: author

The prediction shows a slight decrease in road accident rates in the following months compared to the previous period, ranging from 6,400 to 8,700 accidents. The most accurate forecast oscillates between 7,500 and 8,000 collisions. Wider confidence intervals for lenghty periods reflect the reduced reliability of the prediction, namely for 2026.

4.2 RQ2 results

The procedure for obtaining the results of RQ2 is the same as for RQ1, starting with data analysis.

Figure No.6: Basic data structure for RQ2

```
      Year        Accidents
 Min.   :2000   Min.   : 749227
 1st Qu.:2006   1st Qu.: 936844
 Median :2011   Median : 973055
 Mean   :2011   Mean   :1017395
 3rd Qu.:2016   3rd Qu.:1125738
 Max.   :2022   Max.   :1258878
```

Source: author

The database illustrates annual road accident rates from 2000 to 2022, with an average of 1,017,395 and a median of 973,055. The accident rates peaked at 1,258,878 in 2000 and hit a trough of 749,227 in 2020. The data are identically distributed, with the mean close to the median.

A lack of empirical observations prevents us from visualizing decomposed additive time series. Therefore, we use the Shapiro-Wilk test to select an efficient method and better understand the data structure.

Figure No.7: Results of Shapiro-Wilk test for VRQ2

```
        Shapiro-Wilk normality test

data:  data$Accidents
W = 0.95104, p-value = 0.3075
```

Source: author

The Shapiro-Wilk test confirmed the normal distribution of databased on a p-value higher than 0.05 and W close to 1.
Following the same procedure, the Ramsey RESET test will confirm or reject the linear relationships between the data.

Figure No.8: Results of the RESET test for RQ 2

```
        RESET test

data:  model
RESET = 2.4176, df1 = 2, df2 = 19, p-value = 0.116
```

Source: author

The RESET test showed a value of 2.4176 with a p-value 0.116. The p-value is higher than 0.05, indicating a correctly specified model with no significant non-linearity.
Although the ARIMA model would be ideal for the used methods, not enough empirical observations made us choose the same model as for RQ1 (ETS), which is better for processing less data.

Table No.4 Result of ETS model for RQ2

Parameter	Value
Alpha	0.4791
Beta	1,00E-04
L	1279069.9585
B	-21087.7702
Sigma	50343.94
AIC	575.7472
AICc	579.2766
BIC	581.4247
ME	3071.436
RMSE	45757.26
MAE	31853.51
MPE	0.2122024
MAPE	3.477423
MASE	0.9509206
ACF1	0.163085

Source: author

The ETS model achieved an Alpha of 0.4791 and Beta of 1.00E-04, indicating stability with few changes in the trend. Values of AIC (575.7472), AICc (579.2766) and BIC (581.4247) suggest a decent model fit. The errors (RMSE 45757.26 and MAE 31853.51) are within the expected range, indicating high model stability. The MAPE of 3.48% implies a slight standard error, confirming high model accuracy for the prediction.

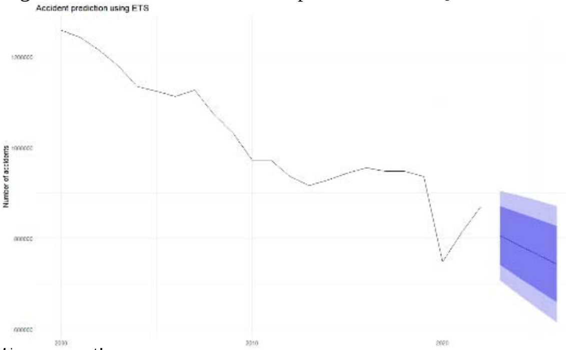
Table 4: ETS model prediction for RQ2

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2023	806757.6	742239.3	871276.0	708085.3	905429.9
2024	785676.9	714134.1	857219.8	676261.6	895092.3
2025	764596.2	686656.9	842535.5	645398.3	883794.1
2026	743515.5	659663.9	827367.2	615275.5	871755.5

Source: author

The prediction of the accident rates for 2023-2026 shows a declining trend, with a point forecast of 806,757.5 accidents per 2023 falling to 743,515.5 in 2026. The confidence intervals suggest expected accident rates ranging between 659,663.9 and 827,367.2 in 2026, with a higher likelihood.

Figure No.9: ETS visualization of prediction for RQ2



Source: author

Our visualization illustrates a long-term decline in road accident rates from 2000 until now, marking the sharpest decrease in 2020, caused by severe movement restrictions during the COVID-19 pandemic. The following predictions for 2023-2026 indicate a slight drop in accident rates over a lengthy period. Blue confidence intervals suggest a possible distribution of predicted values, indicating the most unreliable predictions for more distant years. The annual nature of the data ignores seasonality, predicting only potential road accident rates without seasonal fluctuations.

5 Discussion

RQ1: What will the accident rates be in the Czech Republic withing the following 18 months?

The results of the first research question suggest remarkable trends in the accident rates in the Czech Republic, indicating upward and downward tendencies in road accident rates from 2000 when 2020 marked the sharpest decline. [14] arrived at the same results in her study, attributing the decrease in road accidents and deaths to reduced traffic volumes and severe movement restrictions during the COVID-19 pandemic, influencing long and short-term trends. The accident rates from 2000 to 2018 significantly increased due to higher traffic density and insufficient preventative measures. As of 2019, we have witnessed a downward trend in road accident rates cut by effective defensive measures. Although results show an overall decrease in accident rates, the trend is not strong enough for the Czech Republic to fulfil ‘Vision ZERO’. [11] and [12] reached the same conclusion, pointing to the insufficient strength of this welcome tendency. Opposite results were found by [37], who predicted a steady slight increase in the accident rate in the Czech Republic using neural networks. This increase is attributed to the increasing number of vehicles and the impact of pandemic.

Given the significant non-linearity of the data, we used an ETS model, which was more effective for this type of data [16]. Our results predicted road accident rates for the consecutive 18 months, indicating a slight decrease compared to previous months. The prediction between August 2024 and January 2026 shows average accident rates of about 8,000 per month. The model forecasts a seasonal drop in winter months, mimicking historical data. This seasonal divergence may reflect adverse weather conditions in winter when worsening road conditions make drivers more cautious and traffic less dense.

The model indicates a steady or slightly downward trend in road accident rates in the following months. The estimated accident rates range between 7,000 and 9,000 collisions per month, reflecting the long-term efficiency of preventative measures. The model accuracy may be questioned when an emergency or changes in traffic conditions occur, e.g. the COVID-19 pandemic. Our results are therefore suitable for monitoring trends and potential planning of new measures for increasing road safety.

RQ2: What will the accident rates be in the EU within the following five years?

Our results show that road accident rates in the EU have been declining for a long time, as confirmed by [14]. On the other hand, [17] and [16] arrived at a contrary conclusion by doing similar research in India, suggesting that the measures for reducing road accident rates had been insufficient. Like in the Czech Republic, the COVID-19 pandemic significantly cut the accident rates in the EU, imposing severe movement restrictions and limiting mobility, as confirmed by [21]. The post-pandemic period still keeps road accident rates below the limit of previous years, indicating a continuous improvement of preventative measures on European roads.

Not enough empirical observations made the ARIMA model inapplicable. We chose an ETS model, highly suitable for this type of data fitting [16]. Useful for the data with fewer observations, the model has outstanding parameters for making robust predictions. The resulting AIC, RMSE and MAPE values confirm high model accuracy, proving it suitable for determining long-term goals in the EU road safety sector.

Like in the previous case, the predictions for 2023 – 2026 show a continuous yet slight decline in road accident rates, minimizing the likelihood of fulfilling 'Vision ZERO', as confirmed by [11] and [12]. The EU and its member states' initiatives focused on road safety, like innovating the automotive industry, improving the infrastructure and adopting new legislation, may hugely contribute to the trend. Although the ETS model tries to estimate future tendencies, widening prediction intervals over lengthy periods indicate increased uncertainty in the more distant future.

6 Conclusion

The study focused on predicting road accident rates in the Czech Republic and the EU countries in the following years. We formulated two research questions, answered by an in-depth analysis, fulfilling our research aim.

To answer the first research question, we used an ETS model to deal with non-linear regression of the historical data in the Czech Republic. The model predicted a slightly decreasing trend in the following months, indicating a favorable effect of the measures on reducing accident rates. The prediction showed steadiness and consistent seasonal fluctuations, all considered within the model. Our findings reflect the expectations and public demand for road safety and fulfilling Vision ZERO, a European strategy for regulating accident rates. However, the deadline for meeting the requirements for Vision ZERO is particularly tight, considering the pace at which the Czech Republic cuts its road accident rates.

The second research question explored road accident rates in the EU, revealing a declining trend. We used an ETS model to deal with the lack of empirical observations. Although our results indicate wide intervals over long periods, they provide fertile ground for strategic planning on the European level. Low accident rates significantly reduce negative sentiments road collisions echo in the economy and society. However, like in the previous case, the pace at which the rates decrease will probably be too slow to fulfil Vision ZERO.

Although our study reveals positive findings in the declining trend, zero death rates cannot happen without adopting relevant legislation and raising awareness.

We also had to overcome obstacles like a lack of detailed monthly data from the EU and the model's incapacity to consider emergencies like the COVID-19 pandemic. On the other hand, our analysis provides precious findings for imposing safety measures to reduce road accident rates in the Czech Republic and the EU. The study offers a theoretical and practical model to support effective transport policies meeting the requirements for reasonable road safety.

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Primary Paper Section: A

Secondary Paper Section: AQ