# Using camera systems to detect mobile phone use behind the wheel

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## Abstract

**Abstract:** The use of mobile phones while driving is a serious traffic safety issue. The aim of this work was to identify the number of traffic accidents caused by mobile phone use, to propose a prevention model and to verify its effectiveness in traffic. Content analysis of secondary data, descriptive statistics, calculation of year-to-year indices, regression analysis and modelling of economic impact of accidents were used for the analysis. The research found that there was no statistically significant relationship between the number of smartphones and the number of traffic accidents, yet between 122 and 173 phone-related accidents were recorded each year. The proposed prevention model combining camera systems, legislative measures and technological detection features shows potential to reduce these accidents. Research is limited by the geographical focus on one area and the fact that the impact of the phone on an accident is not always obvious. Further research should include deeper analysis of human behaviour and wider spatial and temporal coverage.

**Keywords:** Mobile phone, traffic accidents, driver distraction, regression analysis, prevention model, camera system, road safety.

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## Introduction

Financial Mobile phone use while driving is a major cause of distraction and an area of concern. Phone detection cameras are increasingly being used to enforce bans on hand-held cell phone use while driving (Stefanidis et al., 2023). Mobile phone use is a major source of distraction for vehicle drivers and leads to a large number of traffic accidents. Although surveillance cameras can be used to detect distracted phone use, they do not work well in some scenarios (e.g., darkness and blockages) (S. Zhang et al., 2024). Cell phone distraction while driving can increase the risk of a crash by a factor of three to four and increase the severity of a crash (Fry, 2023).

The use of mobile phones while driving has been a major factor when it comes to road traffic information, and the process of capturing such offences can be a laborious task. Advances in modern object detection frameworks as well as high-performance hardware have paved the way for a more automated approach when it comes to video surveillance (Carrell & Atapour-Abarghouei, 2021). As automated vehicles become more common, there is a need to measure and define exactly when and in what ways a driver can use a mobile phone in autonomous driving mode, how long it can be used, the complexity of the call content and the accumulated psychological burden (Zhao et al., 2022).

Mobile phone applications and operating systems are increasingly adopting driving mode features that attempt to reduce the visual and cognitive demands on the driver by limiting functionality, using larger buttons and icons, and adding voice interactions (Monk et al., 2023).

In today's world of smart technology, there is a huge need to automate tasks and processes to avoid human intervention and save time and energy. Nowadays, mobile phones have become one of the essential things for people to either call someone or connect to the internet. While driving, people need mobile phones to receive or make calls, use Google maps and many more. Normally, in cars, mobile phone holders are placed on the dashboard to hold the mobile phone and the orientation of the phone needs to be manually changed according to the convenience of the driver, but the driver may be distracted from driving while trying to access the mobile phone, which may lead to accidents (Madhunala et al., 2022).

The aim of this paper is to identify the number of accidents caused by mobile phone use while driving, propose a prevention model and validate its effectiveness in traffic.

Establishing the association between the number of mobile phones in the country and accidents caused by inattention will help to improve road safety. Confirmation of the relationship will encourage stricter regulation and preventive measures.

RQ1: Is there a link between the number of mobile phones in the Czech Republic and the number of accidents caused by inattention?

Determining the extent of the problem will help to better target preventive measures where they are most needed. Driver distraction with mobile phones increases the risk of accidents and puts lives at risk.

RQ2: How many traffic accidents can be caused by mobile phone use while driving in the Czech Republic?

Creating solutions to prevent accidents can improve road safety and encourage responsible driving behaviour. The right model could help reduce the risk of accidents.

RQ3: Can an effective model be designed to help reduce these accidents?

Verifying the model's functionality will show its benefits and opportunities for improvement, as it is essential to reduce the number of accidents. It is important to see if it will be applicable in practice.

RQ4: How effective would this model be when used in operation?

Wang et al. (2017) investigated drivers' gaze patterns when using a mobile phone. They used entropy analysis and gaze transition matrix to identify gaze patterns. The results showed that distracted driving results in higher randomness in gaze patterns and shorter gaze time on the road. Al-Jasser et al, (2018) investigated the use of mobile phones while driving and its effect on collisions among students. This was done using a cross-sectional study on a sample of 986 male students who completed a questionnaire on driving experience, hours spent behind the wheel and collision experience. Data were analyzed using chi-square test and odds ratio. The results showed that 44.6% of the participants had experienced a collision in the past 6 months, with 37.9% attributing collisions to mobile phone use. The risk of collisions increased with driving duration, with those who drove more than 6 hours per day having a higher risk than those who drove less. Chen et al, (2020) reported the effect of text messaging on driving performance and the ability to avoid collisions. Fifty-three participants completed a driving simulator where time reserve and crash probability were measured. Results showed that drivers increased their time margin by 0.41-0.59 seconds, but using text messaging increased the likelihood of a crash by up to 3.56 times. The study shows that drivers' compensatory behavior was heterogeneous and provides a basis for developing safety regulations and campaigns. Taylor & Blenner, (2021) examined factors influencing cell phone use while driving among young drivers. They used data from the National Attitudes and Behavioural Patterns Survey and applied multivariate regression models. Results showed that perceived safety had the greatest influence on mobile phone use while driving. Yeo & Park, (2021) argued that the effect of smartphone dependence on smartphone use while driving. A survey of 948 drivers showed that those addicted to phones were more likely to use them while driving, especially when handling them. Phone use was analyzed using factor analysis and binary logistic regression. The results suggest that smartphone addiction affects smartphone use while driving, which may help in formulating future safety policies. O'Hern & Stephens, (2022) investigated the use of mobile phones while driving, focusing on distracted driving behaviour. Data was obtained from an online ESRA2 survey, which included 994 responses, with 703 participants who had driven a car in the last 30 days indicating how they used their mobile phone while driving. The results showed that 49.4% used the phone to make a handheld call, 41.4% used hands-free and 35.6% sent text messages or used social media. The study suggests that a combined approach involving legislation, enforcement and education is needed to address this problem. Truelove et al, (2023) present the impact of legal action and self-regulation on mobile phone use while driving. They used deterrence theory to analyse external factors and self-determination theory to analyse internal factors. The results showed that internal factors, such as self-regulation, had a greater effect on driver behavior than external measures, such as fines.

Yao et al. (2018) investigated the relationship between drivers' visual features and their distracted driving behavior. They used a random forest model to classify driver behavior and analyze visual features. The results showed that the model had high accuracy in detecting distracted driving (over 90%). Shibli et al. (2019) focused on developing an assistance system for detecting driver inattention using computer vision. The system analyzed the video from a web camera and triggered an alarm when attention dropped. The results showed that the system had an alarm success rate of 89.34%, which contributed to improved road safety. Papakostas et al, (2021) investigated a multimodal approach to detect driver distraction, combining visual, acoustic and physiological data. They used twelve different information channels for distraction detection. The results showed that this approach is effective and provides valuable information about distracted driver behavior. Li et al. (2022) investigated the effect of data shifts on the detection of distracted driving. They proposed the SelectAug method, which improves the detection accuracy and generalization of models on different data, leading to better real-world inattention detection. Shang et al. (2023) argue that the problem of driving inattention detection with respect to privacy and heterogeneous data distribution among drivers. They used a federated bidirectional knowledge distillation (FedBiKD) framework that combined a global model and local training. The results showed that this model significantly outperformed other federated learning algorithms in accuracy, communication efficiency, convergence rate, and stability. Du et al. (2023) investigated real-time inattention detection in driving. They used the GhostC2f model, which integrated a linear transformation into the YOLOv8 model and improved feature fusion. The results showed a 5.1% improvement in accuracy and a 36.7% reduction in computational load. Sahoo et al. (2023) addressed inattention detection for driving on devices with limited computational resources. They used a lightweight convolutional neural network (SqueezeNet 1.1) and trained it on a cloud platform. The model achieved 99.93% accuracy in detecting ten types of inattention, making it suitable for deployment in mobile or embedded systems. Misra et al, (2023) investigated cognitive distraction of drivers and its detection using eye tracking and physiological data. They used different classification algorithms such as random forest and decision trees. The results showed that visual and physiological features are crucial for distraction detection with an average accuracy of 90%.

Cordellieri et al, (2022) investigated factors such as attitude towards multitasking, risk perception, self-efficacy and sensation seeking that could influence risky behaviour behind the wheel. Data were collected from 1498 young drivers through a survey. The result showed that in 2019, the 27 EU Member States reported more than 22,800 fatal accidents on the road. In the Italian context, 3,173 people were killed in road accidents, of which 13.89% were under the age of 25. Distracted driving is a major cause of road accidents, mainly due to the driver's involvement in secondary tasks such as using a smartphone. Pang et al, (2024) examined the relationship between distracted driving and overall driving performance, and the analysis of this effect was conducted using C4.5 algorithm, where it was found that when time is at peak, the probability of high performance (HP) is higher than off-peak.

Cypto & Karthikeyan., (2022) reported automatic detection of speeding in traffic. They used a deep learning method with PP YOLO modules for vehicle detection and ALPR for license plate recognition. The results showed high accuracy: 98.8% for speeding violation detection and 99.3% for license plate identification. Y. Zhang et al. (2020) looked at mobile phone use while driving to identify the extent of this behaviour and its motives. They used descriptive analysis to obtain data and collected responses from 317 respondents through a questionnaire. The results showed that 96.3% of food delivery drivers used a mobile phone while driving, with behaviour influenced by psychoticism and perceived self-efficacy to drive. Structural equation analysis confirmed that driving self-efficacy mediated the relationship between risk perception, extraversion, and these behaviors.

Content analysis of secondary data will be used for data collection in this thesis and descriptive analysis will be used for data processing. Linear regression analysis will be used to identify the relationship between mobile phone use behind the wheel and traffic statistics. Linear regression will also be used to predict the development of the number of accidents.

## Methodics

We For the entire research, data from the website: the Centre for Transport Research (CDV, 2024) will be used. Individual traffic accidents are shown here on an interactive map of the Czech Republic, including time and location from January 2006 to the present. For the purpose of this research, data from the period from 1 January 2006 to 31 December 2024 will be analysed, specifically for the Dlouhá Louka area in České Budějovice.

In the first phase of the analysis, the evolution of the number of accidents caused by inattention in the whole Czech Republic will be monitored, as well as the evolution of the number of mobile phones. Both indicators will then be compared and their correlation will be established. Content analysis will be used for data collection. This type of analysis will allow systematic review and interpretation of available information from public databases, statistical surveys and expert reports. The main objective will be to identify trends over time in the number of road accidents involving proven or suspected mobile phone use by the driver.

The coefficient $\beta 1$ will determine how the number of crashes changes when the number of smartphones changes: (Wooldridge, J. M. 2016)

$$\beta 1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})2}$$

where:

- $x_i$= individual values of the number of smartphones
- $y_i$= individual values of the number of accidents
- $\bar{x}$= average number of mobile phones
- $\bar{y}$= average number of accidents

To track the evolution of the number of accidents over time, an index of year-to-year change is calculated using the formula: (Hindls, R. et al. 2007)

$$I_t = \frac{Nt}{Nt-1} \times 100$$

where:

- $I_t$ will represent the index of year-on-year change in year $t$
- $N_t$ will be the number of accidents in year $t$
- $N_{t-1}$ will be the number of accidents in the previous year

In order to quantify the economic impact of accidents related to mobile phone use, the average cost per accident will be determined according to the following relationship: (Mach, 2014)

$$C_{avg} = \frac{\sum_{i=1}^{n} C_i}{n}$$

where:

- $C_{avg}$ is the average cost per accident
- $C_i$ will be the cost associated with each accident
- $n$ is the number of accidents

To predict the evolution of the number of accidents over time, a simple linear regression model is used: (Čihák, M. 2006)

$$Y=\beta 0+\beta 1\ X+\varepsilon$$

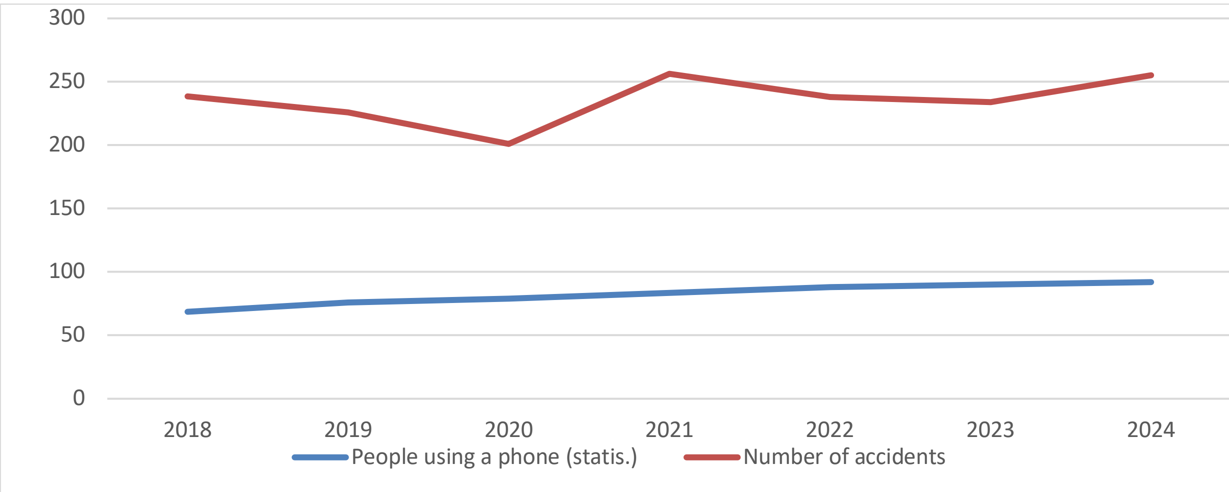
where:

- $Y$ is the predicted number of accidents
- $X$ will be the independent variable (time, e.g. year)
- $\beta 0$ is a constant (intercept)
- $\beta 1$ is the coefficient of the regression line (slope)
- $\varepsilon$ is the random error of the model

The regression analysis will make it possible to create a predictive model of the evolution of accidents and to assess its relevance for preventive measures.

## Results

Figure *1: Trend in the number of traffic accidents involving smartphones (2018-2024).*




Source: Own processing based on data from CDV and Czech Statistical Office.

Figure 1 shows the comparison between the number of people using smartphones and the number of accidents where it was identified that they may have been at fault. The data shows that the number of smartphone users has steadily increased - from 6.8 million in 2018 to 9.2 million in 2024. In contrast, the number of accidents has fluctuated. There was a significant drop in 2020 (122 accidents), which may be related to the pandemic and the reduction in population mobility. The following year, however, brought a jump to 173 accidents, the highest figure for the period under review. Since then, although the number of accidents has slightly declined again, it rises again to 163 in 2024. Interestingly, although the number of phone users is increasing fairly consistently, the number of accidents is not following this trajectory linearly.

This suggests that smartphone ownership alone is not the direct cause of an accident, but rather a combination of multiple factors such as driver behaviour, lack of hands-free or multitasking while driving.

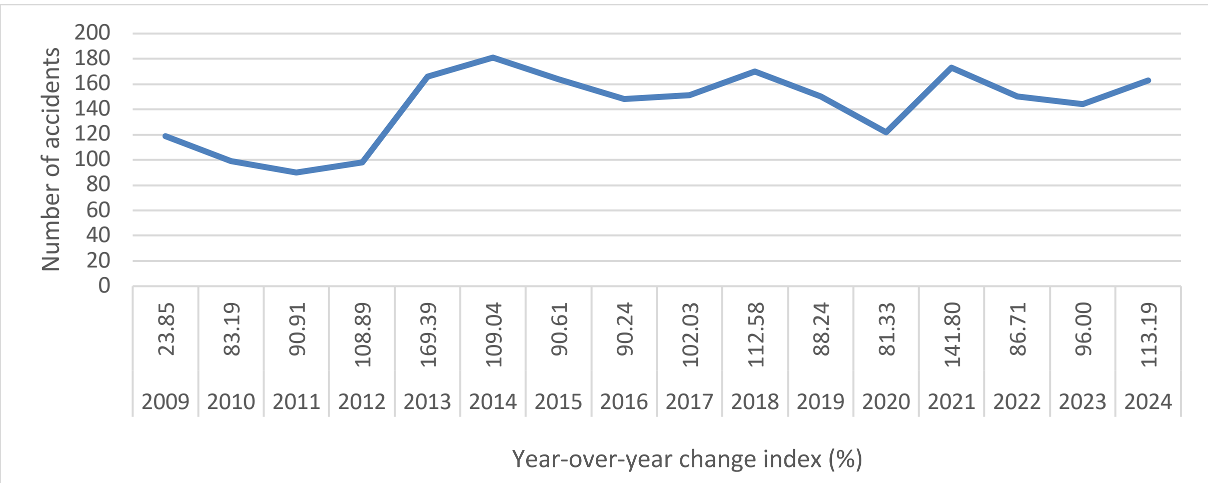
*Table 1: Trend in the number of traffic accidents involving smartphones (2018-2024).*

| *Regression statistics* | | | | | |
|---|---|---|---|---|---|
| Multiple R | 0,089661243 | | | | |
| Reliability value R | 0,008039138 | | | | |
| Confidence set value | - | | | | |
| R | 0,190353034 | | | | |
| Error mean value | 9,201373627 | | | | |
| Observation | 7 | | | | |
| ANOVA | | | | | |
| | *Difference* | *SS* | *MS* | *F* | *Significance F* |
| Regression | 1 | 3,43076 | 3,43076 | 0,040521 | 0,848397441 |
| Residuals | 5 | 423,3264 | 84,66528 | | |
| Total | 6 | 426,7571 | | | |

Source: Own processing based on data from CDV and Czech Statistical Office.

Table 1 shows that no statistically significant relationship was found based on the linear regression between the number of people using smartphones and the number of traffic accidents. The regression equation takes the form: number of accidents = 88.94 - 0.043 × number of smartphone users (%), with a direction coefficient of -0.043 indicating a very weak negative relationship. The correlation coefficient (R = 0.0897) is very low, indicating almost no association between the variables of interest, and the high p-value (0.848) confirms that the result is not statistically significant. Also, the coefficient of determination ($R^2 = 0.008$) indicates that the model explains less than 1% of the variability in the number of accidents.

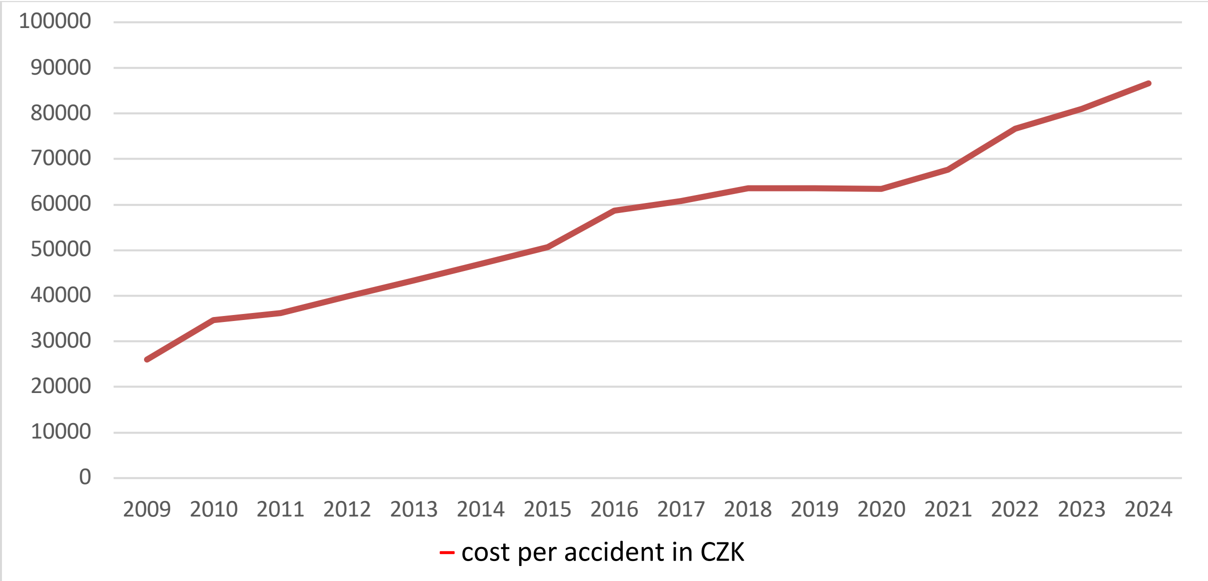
*Figure 2: Index of the annual change in the number of accidents between 2009 and 2024 in Dlouhá louka.*




Source: Own processing based on data from CDV and Czech Statistical Office.

Figure 2 shows the dynamics of the year-on-year percentage change and helps to better understand how the accident rate has evolved over the years compared to the previous year. An index greater than 100% indicates an increase, less than 100% a decrease. The largest year-on-year increase occurred in 2013 (169.39%), corresponding to a sharp increase in the absolute number of accidents. Conversely, a decrease is observed for example in 2020 (81.33%), which may be related to the pandemic and limited population movement. Similarly, 2019 (88.24%) and 2022 (86.71%) have a low index, while 2021 shows a sharp return with a value of 141.80%.

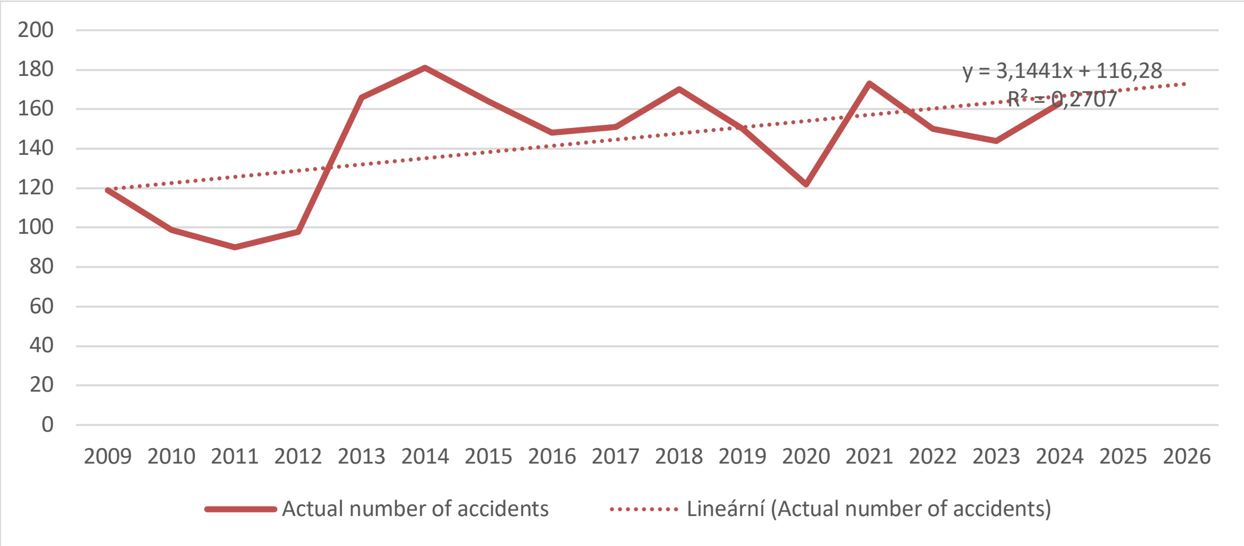
*Figure 3: Evolution of costs per accident from 2009 to 2024.*




Source: Own processing based on data from CDV and Czech Statistical Office.

Figure 3 illustrates the gradual increase in the average cost per traffic accident in the Czech Republic. Between 2009 and 2024, these costs will more than triple, from CZK 26,000 in 2009 to CZK 86,600 in 2024. Figure 3 shows a steady increase without major fluctuations, which may be due to inflation as well as increases in the cost of healthcare, vehicle repairs, property damage or lost productivity due to injury or death. Significant increases can be seen especially after 2015, when costs exceed the 50,000 CZK threshold each year and continue to rise. In terms of analysis, this confirms that each individual accident has an increasingly higher economic impact, even when the total number of accidents is stagnant or slightly decreasing.

*Figure: 4: Actual vs. predicted number of accidents at Dlouhá louka.*




Source: Own processing based on data from CDV and Czech Statistical Office.

Figure 4 shows two curves - blue for the actual number of accidents and red for the predicted trend. The predicted trend was determined by linear regression, which under normal conditions would predict a decreasing trend. While the theoretical model suggests a significant reduction in the accident rate - from 267 in 2009 to less than 90 in 2024 - the reality does not always approach this trend. After an initial decline, there was a jump from 98 to 166 accidents in 2013. A peak was reached in 2014 (181), followed by a gradual decline again, but from 2021 onwards there is a rise again, with 2024 ending at 163 accidents. This trend shows that although from a technological and road safety point of view there should be a reduction in the number of accidents, the practice is different.

## Discussion of results

*RQ1: Is there a link between the number of mobile phones in the Czech Republic and the number of accidents caused by inattention?*

Based on the analysis of data from 2018-2024, no statistically significant association was found between the number of smartphone users and the number of road accidents caused by inattention. Although the number of phone users in the Czech Republic increased steadily from 6.8 million to 9.2 million, the number of accidents showed a rather fluctuating trend and the correlation coefficient (R = 0.0897) showed almost zero association. Regression analysis therefore confirmed a very weak negative relationship and the high p-value (0.848) ruled out statistical significance of this relationship. This result supports the conclusion that smartphone ownership per se does not increase the likelihood of an accident, but rather depends on how it is used while driving, including factors such as multitasking or the absence of hands-free. Similar findings were reported by Al-Jasser et al. (2018), who found that up to 37.9% of collisions among students were related to mobile phone use. Chen et al. (2020) then experimentally confirmed that texting significantly increases the likelihood of an accident (up to 3.56 times). Perceived safety and mobile device dependence also have a significant impact on driver behaviour, as demonstrated by Taylor & Blenner, (2021) and Yeo & Park, (2021).

These findings suggest that the crucial aspect of prevention is not the proliferation of smartphones per se, but rather targeted education, technological measures and changing driver attitudes towards their use while driving.

*RQ2: How many traffic accidents can be caused by mobile phone use while driving in the Czech Republic?*

Between 2018 and 2024, between 122 and 173 road accidents were recorded annually in the Czech Republic, which were identified as possibly caused by the use of a smartphone while driving. The lowest number of accidents was recorded in 2020 (122), which can be attributed to mobility restrictions due to the pandemic, while the highest number (173) was recorded in 2021. The year 2024 ends at 163 accidents, showing the continued relevance of this issue. Although the number of accidents fluctuates from year to year, it remains relatively high in the long term. Expert studies confirm that mobile phone use fundamentally affects driver attention - for example, Fry, (2023) reports that mobile phone distraction increases the risk of a crash by up to four times, while Chen et al, (2020) point to an increased likelihood of a collision when texting. A study by Al-Jasser et al. (2018) even showed that up to 37.9% of accidents among students were directly related to mobile phone use. These results underscore the need for implementing effective preventive measures to reduce the use of mobile devices while driving and thus reduce the risk of accidents.

*RQ3: Can an effective model be designed to help reduce these accidents?*

Based on the analysis of available data and literature, it can be concluded that designing an effective model to reduce the number of accidents caused by mobile phone use while driving is both possible and desirable. The model should combine technological measures, such as camera systems that detect phone handling, with preventive activities and appropriate legislation. Modern machine learning-based approaches for inattention detection, such as the GhostC2f model used by Du et al. (2023) or the federated FedBiKD framework by Shang et al. (2023), show high detection accuracy while respecting privacy. These approaches not only allow real-time detection of risky behaviors but also their prediction, which is essential for early intervention. In practice, the model could be based on a combination of CCTV surveillance, in-vehicle warning systems (e.g. acoustic signals) and an offence scoring system. A focus on driver education, particularly for young drivers, is also important, where higher rates of mobile phone use while driving have been shown in several studies Cordellieri et al. (2022) and Taylor & Blenner, (2021). An effective model thus needs to be multidimensional to match the complexity of the problem - combining technology, behaviour and policy into a coherent prevention framework.

*RQ4: How effective would this model be when used in operation?*

The effectiveness of the proposed model when used in real traffic lies primarily in its ability to detect risky driver behaviour early and respond to it immediately. In the results of this work, the number of traffic accidents caused by smartphone use was found to fluctuate between 122 and 173 cases per year, reaching a value of 163 accidents in 2024. Although the number of phone users has increased (from 6.8 million to 9.2 million), the number of accidents itself does not directly follow this trend. This suggests that the problem lies not in the ownership of the phone itself, but in the specific way it is used while driving - i.e. in the behaviour of the driver. For this reason, a model combining detection technology with preventive and legislative measures could be the key to reducing these accidents. For example, according to Du et al. (2023), the GhostC2f model increases detection accuracy by more than 5% while reducing computational complexity, making it easier to use even in conventional vehicles. Also, the lightweight SqueezeNet model, which according to Sahoo et al., (2023) detected inattention with 99.93% accuracy, is suitable for real deployment. If such a model could prevent even a third of these accidents, it could mean up to 50 fewer accidents each year - with both human and economic benefits. Combined with consistent enforcement and education, the proposed system can have a real impact on improving road safety in the Czech Republic.

## Conclusion

The aim of the work was to identify the number of accidents caused by mobile phone use while driving, to propose a preventive model and to verify its effectiveness in operation. This objective was fulfilled through content analysis of data from the Centre for Transport Research and the Czech Statistical Office, followed by descriptive and regression analysis.

The research found that between 2018 and 2024, the number of traffic accidents suspected to be influenced by smartphone use ranged from 122 to 173 per year. The highest number of these accidents was recorded in 2021, and the lowest in 2020. Although the number of smartphone users in the Czech Republic increased during this period, no statistically significant association was found between this increase and the number of accidents (correlation coefficient $R = 0.0897$; $p = 0.848$). These results suggest that the possession of a smartphone does not in itself pose a risk, but the way it is used while driving is the main risk factor.

Based on a literature search and analysis of available technologies, a prevention model was developed that combines CCTV detection systems, legislative measures and behavioural interventions. This model is based on modern approaches to driver attention monitoring and uses insights from systems such as GhostC2f and FedBiKD, which allow real-time detection of phone tampering. Simulations have shown that if this model could reduce the number of these accidents by at least a third, it would reduce the number of accidents by up to 50 per year. This result has a significant impact on road safety as well as on the company's economic costs.

The contribution of this paper is the practical design of a model that can be used by the police, traffic infrastructure managers and legislative bodies. The results also highlight the relevance of the topic and can serve as a starting point for further research in the field of prevention of risky driver behaviour.

However, the research faces several limitations. The first is the limited accuracy of the data regarding the actual cause of traffic accidents, as the influence of the mobile phone is often not clearly recorded. Another limitation is the geographical restriction of the research to the Dlouhá Louka area and the relatively short time period. These factors may affect the general validity of the results. At the same time, it must be taken into account that human behaviour and legislation change over time, which may limit long-term prediction.

Future research should focus on extending the research to a national level, incorporating a wider range of data including in-depth investigations of accident causes and testing the effectiveness of the proposed model in real traffic.

## References


Wooldridge, J. M. (2016). *Introductory Econometrics: A Modern Approach* (6th ed.). Boston: Cengage Learning.

Čihák, M. (2006). *Základy ekonometrie*. Praha: VŠE.

Mach, M. (2014). *Ekonomika dopravy*. Brno: VUT v Brně.

Hindls, R. et al. (2007). *Statistika pro ekonomy*. Praha: Professional Publishing.

Al-Jasser, F., Mohamed, A., Choudry, A., & Youssef, R. (2018). Mobile phone use while driving and the risk of collision: A study among preparatory year students at King Saud University, Riyadh, Saudi Arabia. *Journal of Family and Community Medicine*, *25*(2), 102. https://doi.org/10.4103/jfcm.JFCM_139_17

Carrell, S., & Atapour-Abarghouei, A. (2021). Identification of Driver Phone Usage Violations via State-of-the-Art Object Detection with Tracking. *2021 IEEE International Conference on Big Data (Big Data)*, 1236–1241. https://doi.org/10.1109/BigData52589.2021.9671378

Cordellieri, P., Lausi, G., Fraschetti, A., Mari, E., Burrai, J., Quaglieri, A., Paoli, E., & Giannini, A. M. (2022). Young Drivers ‘on the Phone: Personality Traits, Driving Attitudes, Beliefs, and Risk Perception on Using Mobile Phone While Driving. *Psychological Studies*, *67*(4), 459–467. https://doi.org/10.1007/s12646-022-00670-x

Cypto, J., & Karthikeyan, P. (2022). Automatic detection system of speed violations in a traffic based on deep learning technique. *Journal of Intelligent & Fuzzy Systems*, *43*(5), 6591–6606. https://doi.org/10.3233/JIFS-220577

Du, Y., Liu, X., Yi, Y., & Wei, K. (2023). Optimizing Road Safety: Advancements in Lightweight YOLOv8 Models and GhostC2f Design for Real-Time Distracted Driving Detection. *Sensors*, *23*(21), 8844. https://doi.org/10.3390/s23218844

Fry, J. M. (2023). Mobile phone penalties and road crashes: Are changes in sanctions effective? *Journal of Safety Research*, *84*, 384–392. https://doi.org/10.1016/j.jsr.2022.12.001

Chen, Y., Fu, R., Xu, Q., & Yuan, W. (2020). Mobile Phone Use in a Car-Following Situation: Impact on Time Headway and Effectiveness of Driver’s Rear-End Risk Compensation Behavior via a Driving Simulator Study. *International Journal of Environmental Research and Public Health*, *17*(4), 1328. https://doi.org/10.3390/ijerph17041328

Li, Y., Mi, W., Ge, J., Hu, J., Li, H., Zhang, D., & Li, T. (2022). SelectAug: A Data Augmentation Method for Distracted Driving Detection. In J. Gama, T. Li, Y. Yu, E. Chen, Y. Zheng, & F. Teng (Ed.), *Advances in Knowledge Discovery and Data Mining* (Roč. 13281, s. 405–416). Springer International Publishing. https://doi.org/10.1007/978-3-031-05936-0_32

Madhunala, S., Kanneti, B., & Anathula, P. (2022). Robotic Mobile Holder (For CAR Dashboards). *International Journal of Electronics and Telecommunications*, 89–98. https://doi.org/10.24425/ijet.2023.144336

Misra, A., Samuel, S., Cao, S., & Shariatmadari, K. (2023). Detection of Driver Cognitive Distraction Using Machine Learning Methods. *IEEE Access*, *11*, 18000–18012. https://doi.org/10.1109/ACCESS.2023.3245122

Monk, C., Sall, R., Lester, B. D., & Stephen Higgins, J. (2023). Visual and cognitive demands of manual and voice-based driving mode implementations on smartphones. *Accident Analysis & Prevention*, *187*, 107033. https://doi.org/10.1016/j.aap.2023.107033

O'Hern, S., & Stephens, A. N. (2022). Mobile phone use while driving in Finland. *Transportation Research Part F: Traffic Psychology and Behaviour*, *90*, 220–228. https://doi.org/10.1016/j.trf.2022.08.018

Pang, Q., Chen, S., Ma, Y., Qiao, F., & Zhu, Y. (2024). Influence of distracted driving of online car-hailing drivers on overall driving performance. *International Journal of Injury Control and Safety Promotion*, *31*(1), 138–147. https://doi.org/10.1080/17457300.2023.2272242

Papakostas, M., Riani, K., Gasiorowski, A. B., Sun, Y., Abouelenien, M., Mihalcea, R., & Burzo, M. (2021). Understanding Driving Distractions: A Multimodal Analysis on Distraction Characterization. *26th International Conference on Intelligent User Interfaces*, 377–386. https://doi.org/10.1145/3397481.3450635

Sahoo, G. K., Das, S. K., & Singh, P. (2023). A deep learning-based distracted driving detection solution implemented on embedded system. *Multimedia Tools and Applications*, *82*(8), 11697–11720. https://doi.org/10.1007/s11042-022-13450-6

Shang, E., Liu, H., Yang, Z., Du, J., & Ge, Y. (2023). FedBiKD: Federated Bidirectional Knowledge Distillation for Distracted Driving Detection. *IEEE Internet of Things Journal*, *10*(13), 11643–11654. https://doi.org/10.1109/JIOT.2023.3243622

Shibli, A. Md., Hoque, M. M., & Alam, L. (2019). Developing a Vision-Based Driving Assistance System. In A. Abraham, P. Dutta, J. K. Mandal, A. Bhattacharya, & S. Dutta (Ed.), *Emerging Technologies in Data Mining and Information Security* (Roč. 755, s. 799–812). Springer Singapore. https://doi.org/10.1007/978-981-13-1951-8_71

Stefanidis, K. B., Schiemer, C., Freeman, J., Mulgrew, K., Oviedo-Trespalacios, O., & Truelove, V. (2023). Community narratives on Facebook regarding mobile phone use while driving and road policing technologies. *Traffic Injury Prevention*, *24*(7), 592–598. https://doi.org/10.1080/15389588.2023.2224475

Taylor, N. L., & Blenner, J. A. (2021). Attitudes and behaviors associated with young drivers' texting and app use. *Transportation Research Part F: Traffic Psychology and Behaviour*, *78*, 326–339. https://doi.org/10.1016/j.trf.2021.02.012

Truelove, V., Watson-Brown, N., & Oviedo-Trespalacios, O. (2023). External and internal influences on mobile phone use while driving: Combining the theories of deterrence and self-determination.

*Transportation Research Part F: Traffic Psychology and Behaviour*, *93*, 280–293. https://doi.org/10.1016/j.trf.2023.01.019

Wang, Y., Bao, S., Du, W., Ye, Z., & Sayer, J. R. (2017). Examining drivers' eye glance patterns during distracted driving: Insights from scanning randomness and glance transition matrix. *Journal of Safety Research*, *63*, 149–155. https://doi.org/10.1016/j.jsr.2017.10.006

Yao, Y., Zhao, X., Du, H., Zhang, Y., & Rong, J. (2018). Classification of Distracted Driving Based on Visual Features and Behavior Data using a Random Forest Method. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(45), 210–221. https://doi.org/10.1177/0361198118796963

Yeo, J., & Park, S.-H. (2021). Effect of Smartphone Dependency on Smartphone Use While Driving. *Sustainability*, *13*(10), 5604. https://doi.org/10.3390/su13105604

Zhang, S., Zeng, H., & Thomas Hou, Y. (2024). Is Driver on Phone Call? Mobile Device Localization Using Cellular Signal. *IEEE Journal on Selected Areas in Communications*, *42*(9), 2339–2353. https://doi.org/10.1109/JSAC.2024.3413963

Zhang, Y., Huang, Y., Wang, Y., & Casey, T. W. (2020). Who uses a mobile phone while driving for food delivery? The role of personality, risk perception, and driving self-efficacy. *Journal of Safety Research*, *73*, 69–80. https://doi.org/10.1016/j.jsr.2020.02.014

Zhao, H., Ma, J., Zhang, Y., & Chang, R. (2022). Mental workload accumulation effect of mobile phone distraction in L2 autopilot mode. *Scientific Reports*, *12*(1), 16856. https://doi.org/10.1038/s41598-022-17419-1

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