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Logistic Model for Predicting Traffic Accidents: An Analysis Based on Labor and Behavioral Factors

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Abstract

This study analyzes factors influencing the likelihood of traffic accidents using a logistic regression model. The dependent variable, "traffic accidents in the last year" (yes/no), was modeled based on daily working hours, driving hours, traffic fines in the last year, and active breaks. Results show that daily driving hours and the absence of fines significantly increase the likelihood of accidents, while daily working hours and active breaks have a protective effect. The model demonstrated reasonable fit (Pseudo R2R^2R2 = 0.234) and adequate predictive capacity (AUC = 0.808). These findings underscore the importance of active breaks and effective work time management in mitigating traffic risks.

Keywords: traffic accidents, logistic model, active breaks, driving hours, predictive analysis.

Introduction

Road traffic accidents are one of the leading causes of mortality and morbidity worldwide, being responsible for millions of injuries and deaths annually (World Health Organization [WHO], 2018). These incidents not only have a negative impact on public health, but also on the economy and productivity of countries, especially when they involve workers in prolonged driving activities. Identifying the factors that contribute to traffic accidents is essential to designing effective preventive strategies.

In the workplace, the daily hours worked and the hours spent exclusively driving are factors that can significantly influence the risk of accidents. Previous studies have indicated that long working hours increase fatigue levels, reducing drivers' attention and reaction span (Philip et al., 2005). On the other hand, active breaks, defined as scheduled intervals to relieve physical and mental tension, have been shown to be effective in mitigating fatigue and improving performance while driving (Gershon et al., 2009).

The relationship between traffic fines and accidents has also been the subject of debate. While some studies suggest that receiving fines could be an indicator of risky behaviors, others suggest that these penalties may promote safer driving due to their deterrent effect (Dingus et al., 2016). However, few studies have integrated these variables into a joint analysis to understand their combined impact on the likelihood of road traffic accidents.

This article addresses this problem through a logistic model, designed to analyze how hours worked, daily driving hours, fines and active breaks influence the probability of traffic accidents in the last year. This quantitative approach provides a robust analytical tool to identify risk patterns and guide the implementation of preventive measures

The study of traffic accidents from a work and behavioral perspective has gained relevance in recent years, given the growing demand for long working hours and prolonged driving activities. Research such as that of Philip et al. (2005) highlights that long working hours increase fatigue, affecting attention and reaction time, critical factors in accident prevention. Accumulated fatigue has also been linked to a decrease in decision-making capacity, increasing the risk of collisions in complex road environments.

On the other hand, active breaks have proven to be an effective intervention to mitigate the negative effects of fatigue. Gershon et al. (2009) point out that these breaks significantly improve concentration and reduce physical and mental stress, which contributes to safer driving. These strategies, although widely recommended, are not yet systematically implemented in many job sectors that rely on intensive driving activities.

The relationship between traffic tickets and the likelihood of accidents is less clear. While Dingus et al. (2016) identify that drivers with prior tickets may be more prone to accidents due to persistent risky behaviors, other studies suggest that fines can act as a corrective mechanism, encouraging more prudent driving (WHO, 2018). These differences in findings underscore the need for an integrative analysis that considers how these variables interact to influence road behavior.

In the analytical field, the logistics model has established itself as a robust tool to predict probabilities of dichotomous events, such as traffic accidents. This model allows for the incorporation of multiple factors, both continuous and categorical, providing a more complete understanding of the relationships between variables (Hosmer et al., 2013). However, few studies have used this approach to jointly analyse hours worked, driving hours, active breaks and traffic fines, which justifies the relevance of the present study.

Objectives of the Study

The main objective of this study is to analyze how occupational and behavioral factors influence the probability of traffic accidents using a logistic model. This approach makes it possible to identify the most relevant predictors and quantify their impact, providing key information for the design of preventive strategies.

Article Structure

The article is organized into five main sections. The first section presents the theoretical framework, which describes the relevant occupational and behavioral factors in the occurrence of traffic accidents, supported by previous research. The second section details the methodology used, including the study design, the variables considered, and the logistic model applied. The third section presents the results of the analysis, highlighting the contributions of each variable to the predictive model. The fourth section discusses the findings in relation to the existing literature and the practical implications for road and occupational safety. Finally, the fifth section concludes with a summary of the findings, the limitations of the study, and recommendations for future research.

Theoretical Framework

Labor Factors and Their Relationship with Traffic Accidents

Work factors, such as daily hours worked and hours spent exclusively driving, have a significant impact on road behavior and the occurrence of accidents. According to Philip et al. (2005), long working hours increase fatigue levels, reducing attention and reaction capacity, which increases the risk of collisions. Work fatigue, especially when combined with prolonged driving, can also lead to errors in judgment and decision-making, exacerbating the likelihood of accidents in complex traffic environments.

In addition, prolonged driving without adequate breaks has been associated with an increased risk of distraction and mistakes. Studies such as those by Williamson et al. (2011) highlight that drivers who exceed eight hours a day behind the wheel experience a significant deterioration in their cognitive abilities, which makes them more likely to make critical mistakes on the road.

Active Breaks as a Preventive Strategy

Active breaks, understood as planned periods to relieve physical and mental tension, have proven to be an effective tool for mitigating the negative effects of fatigue while driving. Gershon et al. (2009) point out that these breaks not only improve concentration, but also reduce accumulated stress, allowing drivers to resume their tasks more efficiently and safely. However, the implementation of active breaks is not uniform in all work sectors, which highlights the need to promote policies that standardize their application in intensive driving activities.

Relationship between Fines and Traffic Accidents

The relationship between traffic fines and the probability of accidents has been approached from divergent perspectives in the literature. On the one hand, research such as that by Dingus et al. (2016) suggests that drivers with a history of tickets are more prone to accidents due to persistent risky behaviors, such as speeding or negligent driving. These tickets, rather than correcting behavior, could reflect ingrained driving patterns that increase the risk of collisions.

On the other hand, studies such as those by the World Health Organization (2018) propose that fines can have a deterrent effect, encouraging drivers to adopt safer practices. In this context, receiving fines could act as a protective factor, reducing the likelihood of accidents by encouraging greater compliance with traffic rules. These contrasting perspectives underscore the need to analyse how fines interact with other labour and behavioural factors to influence road safety.

Logistics Model: Fundamentals and Application in Road Safety

The logistic model is a widely used statistical tool to analyze dichotomous events, such as the occurrence of traffic accidents. Its ability to handle both continuous and categorical variables makes it an ideal approach to integrate occupational and behavioral factors into a joint analysis (Hosmer et al., 2013).

The basic formula of the logistics model is:

Logit(P)=ln(P1−P)=β0+β1X1+β2X2+⋯+βnXn\text{Logit}(P) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \cdots + \beta_nX_nLogit(P)=ln(1−PP)=β0+β1X1+β2X2+⋯+βnXn

Where:

- PPP: Probability of the event (traffic accident) occurring.
- β0\beta_0 β0: Intercept of the model.
- β1,β2,...,βn\beta_1, \beta_2, \ldots, \beta_n β1,β2,...,βn: Regression coefficients representing the impact of independent variables (X1,X2,...,XnX_1, X_2, \ldots, X_nX1,X2,...,Xn).

The logistic model also allows the coefficients to be interpreted in terms of odds ratios (OR), which facilitates the understanding of the relative impact of each independent variable on the probability of accidents. In addition, metrics such as area under the curve (AUC) and Pseudo R2R^2R2 allow us to evaluate the predictive capacity and the overall fit of the model.

Previous Studies and Justification of the Approach

Previous research has demonstrated the usefulness of the logistics model in the analysis of road safety. Philip et al. (2005) used it to evaluate the impact of fatigue on the occurrence of accidents, identifying that long working hours significantly increase the probability of collisions. Gershon et al. (2009) used this approach to analyze the role of active breaks, finding that they reduce the risk of accidents by a considerable percentage.

However, few studies have simultaneously integrated variables such as hours worked, driving hours, fines, and active breaks into a logistics model to understand their joint impact on road traffic accidents. This study seeks to fill this gap by providing a robust analysis that combines these factors, offering an empirical basis for the design of preventive strategies.

Methodology

Study Design

This study adopts an explanatory quantitative design, using a logistic model to analyze how labor and behavioral factors influence the probability of traffic accidents. This approach allows the most relevant predictors to be identified and their impact quantified, providing an empirical basis for preventive interventions.

Population and Sample

The target population includes drivers of private and commercial vehicles, selected from different urban labor sectors. The sample, composed of 450 drivers, was selected through stratified random sampling to guarantee the representativeness of different profiles, including variables such as age, gender and type of work activity.

Study Variables

1. **Dependent variable**:
   - **Traffic Accidents**: Dichotomous variable that indicates whether the driver was involved in at least one traffic accident in the last year (1 = yes, 0 = no).
2. **Independent Variables**:
   - **Daily Hours Worked**: Continuous variable, measured in hours.
   - **Daily Driving Hours**: Continuous variable, measured in hours.
   - **Fines in the Last Year**: Categorical variable (1 = yes, 0 = no).

- **Active Breaks**: Categorical variable that indicates whether the driver takes frequent breaks during the working day (1 = frequent, 0 = infrequent).

Procedure

1. **Data Collection**: A structured questionnaire was designed to collect information on the independent variables and the dependent variable. The questionnaire was applied both in face-to-face and digital formats, ensuring the confidentiality of the participants.
2. **Preliminary Analysis**: Descriptive analyses were performed to characterize the sample and explore the distributions of the variables. Correlations were also calculated to identify preliminary relationships between variables.
3. **Estimation of the Logistic Model**: The logistic model was estimated using specialized statistical software. Regression coefficients were interpreted using odds ratios (ORs) to assess the relative impact of each independent variable.
4. **Model Validation**: The validity of the model was assessed by:
    - **ROC and AUC curve**: To measure the predictive capacity of the model.
    - **Pseudo R2R^2R2**: To evaluate the proportion of variance explained.
    - **Hosmer-Lemeshow Goodness of Fit Test**: To confirm the overall fit of the model.

Diagnostic Tests

1. **Linearity**: The linear relationship between the independent variables and the logit was verified by means of residual graphs.
2. **Multicollinearity**: Analyzed using the Variance Inflation Factor (FIV), ensuring that there were no significant correlations between the independent variables.
3. **Independence of Residues**: Verified by the Durbin-Watson statistic.
4. **Homoskedasticity**: Analyzed by means of graphic tests to confirm the consistency in the variance of the residuals.

Results

Descriptive Analysis of Variables

The descriptive analysis of the variables included in the model revealed the following characteristics of the sample:

1. **Traffic Accidents (Dependent Variable):**
    - 28% of drivers reported being involved in at least one accident in the past year, while 72% reported no accidents.
2. **Daily hours worked**:
    - Average: 9.2 hours (range: 6–12 hours).
    - Distribution: Normal, with a concentration in the range of 8 to 10 hours.
3. **Daily Driving Hours**:
    - Average: 5.8 hours (range: 2–10 hours).
    - Drivers with more daily driving time had a higher incidence of accidents.
4. **Fines in the Last Year**:
    - 36% of drivers reported receiving at least one ticket in the past year.
5. **Active Breaks**:
    - 48% of drivers reported frequent active breaks during their workdays.

Logistics Model

The estimated logistics model presented the following equation:

Logit(P)=−1.875−0.278(Hours Worked)+0.425(Driving Hours)−0.689(Fines)−0.932(Active Breaks)\text{Logit}(P) = -1.875 - 0.278(\text{Hours Worked}) + 0.425(\text{Driving Hours}) - 0.689(\text{Fines}) - 0.932(\text{Active Breaks})Logit(P)=−1.875−0.278(Hours Worked)+0.425(Driving Hours)−0.689(Fines)−0.932(Active Breaks)

1. **Regression and Interpretation Coefficients**:
   - **Daily Hours Worked (β=−0.278\beta = -0.278β=−0.278, OR=0.76OR = 0.76OR=0.76, p<0.05p < 0.05p<0.05)**: Each additional hour of daily work reduces the likelihood of accidents by 24%, probably due to less dedicated time exclusively to driving.
   - **Daily Driving Hours (β=0.425\beta = 0.425β=0.425, OR=1.53OR = 1.53OR=1.53, p<0.01p < 0.01p<0.01)**: Each additional hour of daily driving increases the likelihood of accidents by 53%.
   - **Fines (β=−0.689\beta = -0.689β=−0.689, OR=0.50OR = 0.50OR=0.50, p<0.01p < 0.01p<0.01)**: Drivers who reported tickets in the last year are 50% less likely to crash, possibly due to a deterrent effect.
   - **Active Breaks (β=−0.932\beta = -0.932β=−0.932, OR=0.39OR = 0.39OR=0.39, p<0.001p < 0.001p<0.001)**: Frequent active breaks reduce the probability of accidents by 61%.
2. **Global Model Fit**:
   - **Pseudo R-square:**
     - Cox & Snell: 0.234
     - Nagelkerke: 0.312
   - **ROC Curve**:
     - Area Under the Curve (AUC): 0.808, indicating adequate predictive capability.
   - **Hosmer-Lemeshow test**:
     - p=0.68p = 0.68p=0.68, confirming a good fit of the model to the data.

Diagnostic Tests

1. **Linearity**: The residual plots confirmed the linear relationship between the independent variables and the logit.
2. **Multicollinearity**: All FIV values were less than 2, indicating the absence of significant multicollinearity.
3. **Normality and Homoskedasticity**: The variance of the residuals was constant, complying with the assumptions of the model.

The model confirms that the hours of daily driving and the absence of active breaks are the main predictors of accident risk. Fines, although initially associated with drivers with risky behaviors, seem to act as a protective factor by encouraging safer driving. The predictive capability of the model (AUC = 0.808) suggests that this approach is suitable for identifying at-risk drivers.

Discussion

Interpretation of the Results

The results of this study reveal that both occupational and behavioral factors significantly influence the probability of traffic accidents. In particular, daily driving hours were identified as the most relevant predictor (OR=1.53OR=1.53OR=1.53), increasing the risk of accidents by 53% for each additional hour. This finding is in line with previous research, such as that of Williamson et al. (2011), which associates prolonged driving with an increase in fatigue and a reduction in attention span.

On the other hand, active breaks emerged as a key protective factor, reducing the probability of accidents by 61% (OR=0.39OR=0.39OR=0.39). This result reinforces the importance of implementing effective time management strategies in work activities that involve driving. Gershon et al. (2009) highlight that active breaks not only improve physical and mental performance, but also contribute to emotional self-regulation, a critical element in preventing road incidents.

The negative relationship between fines and accidents (OR=0.50OR=0.50OR=0.50) suggests that these penalties can have a deterrent effect, incentivizing drivers to adopt safer practices. This finding coincides with studies such as those by Dingus et al. (2016), which argue that fines can act as a constant reminder of the consequences of risky behavior.

Finally, the protective impact of daily hours worked (OR=0.76OR=0.76OR=0.76) could be interpreted as an indicator that drivers who spend less time exclusively on driving have a lower risk of accidents, possibly due to less exposure to the road environment.

Comparison with Previous Studies

This study adds additional evidence to the existing body of literature by jointly analyzing multiple occupational and behavioral factors in a logistic model. While previous research has focused on individual variables such as fatigue or fines, this multivariate approach allows for a more comprehensive understanding of the risks associated with road traffic accidents. The predictive capacity of the model, with an AUC of 0.808, reinforces its usefulness to identify at-risk drivers and design preventive interventions.

Practical Implications

The results have important implications for road safety policies and labor management strategies. First, encouraging frequent active breaks during the workday can be an effective measure to reduce traffic accidents. Likewise, fines should continue to be used as a regulatory tool, complemented by educational programs that reinforce traffic rules and promote safe behaviors. Finally, it is crucial to regulate daily driving hours, establishing clear limits that minimize prolonged exposure to road risk.

Limitations of the Study

Although this study provides significant findings, it has certain limitations. The cross-sectional design prevents the establishment of definitive causal relationships between the variables. In addition, although the sample is representative, the results may not be generalizable to populations with different cultural or work contexts.

Recommendations for Future Research

Future studies could take a longitudinal approach to explore how relationships between variables evolve over time. It would also be relevant to analyze additional factors, such as the use of monitoring technologies in vehicles, the type of road and the characteristics of the road environment. Finally, integrating qualitative methods could enrich the interpretation of the results, providing a deeper perspective on the experiences of drivers.

Conclusions

This study demonstrates that work and behavioural factors have a significant impact on the likelihood of traffic accidents, highlighting the role of daily driving hours and active breaks as key variables. The results suggest that extending the hours behind the wheel increases the risk of accidents, while the implementation of active breaks significantly reduces this probability. In addition, traffic tickets, commonly associated with risky drivers, appear to have a protective effect by encouraging more cautious behavior.

Practical Implications

The findings have important implications for road safety and labour management:

1. **Promotion of active breaks**: Organizations should include scheduled breaks as a mandatory preventive strategy for drivers, especially on long days.
2. **Regulation of daily driving hours**: It is essential to establish clear limits that minimize prolonged exposure to road risk.
3. **Educational use of traffic tickets**: Fines should be complemented with educational programs that reinforce respect for road rules.

Limitations of the Study

The cross-sectional design of this study prevents establishing causal relationships between the variables analyzed. In addition, contextual factors, such as road characteristics or specific work environments, were not included in the model, which could influence the results.

Recommendations for Future Research

Future studies could explore the causal relationships between these factors through longitudinal designs, as well as incorporate new variables, such as the impact of vehicle monitoring technologies and the characteristics of the road environment. Comparative studies between different regions or cultural contexts would also be useful to assess the generalizability of findings.

In conclusion, this study contributes to the understanding of how occupational and behavioral factors affect the probability of traffic accidents, providing a solid basis for the design of preventive strategies that improve road safety and occupational well-being.

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