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Logistic Model for Predicting Traffic Fines: A Statistical Approach to Demographic and Behavioral Factors

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Abstract

This study uses a logistic regression model to analyze the factors influencing the likelihood of receiving traffic fines within a year. The dichotomous dependent variable (yes/no) was modeled based on independent variables such as age, previous accidents, rest and vacation, active breaks, and general intensity. The results indicate that lack of rest, previous accidents, and absence of active breaks significantly increase the likelihood of receiving fines, while age and general intensity act as protective factors. The model demonstrated robust fit (AUC = 0.9101) and a Pseudo R-squared between 45.6% and 61.2%, showcasing its predictive capability. These findings can inform strategies to reduce traffic violations through interventions in driving habits and workplace wellness.

Keywords: logistic model, traffic fines, active breaks, rest, statistical prediction.

Introduction

Traffic fines represent one of the main strategies to regulate road behavior and reduce the incidence of accidents on the roads. However, despite regulatory efforts, recidivism in infractions continues to be a challenge for the authorities, reflecting the complexity of the factors that affect the behavior of drivers. From a behavioral and demographic perspective, elements such as age, previous experience with accidents, quality of rest, and active breaks emerge as possible determinants of traffic violations (World Health Organization [WHO], 2018).

In the workplace, especially in sectors that demand high driving intensity, the relationship between working conditions and traffic offences is particularly relevant. Previous research has indicated that lack of adequate rest, long working hours, and the absence of stress-mitigating strategies negatively affect attention and decision-making behind the wheel (Dingus et al., 2016). However, there is still a gap in the literature regarding how these factors interact to influence the probability of receiving traffic tickets, which justifies the need for studies that integrate these variables into a predictive model.

This article addresses this problem through a logistic model that analyzes the probability of receiving traffic fines based on demographic and behavioral factors. By employing a quantitative approach, the study seeks not only to identify the most relevant factors, but also to quantify their impact, providing key information to design preventive and corrective strategies in the road and labor fields.

The analysis of road behaviour and traffic offences has been the subject of multiple studies in the fields of psychology, road safety and epidemiology. One of the most consistent factors in the literature is the relationship between the driver's age and the probability of committing infractions. According to research by the World Health Organization (WHO, 2018), young drivers are typically more likely to receive fines due to risky behaviors and less experience behind the wheel, while older drivers tend to adopt safer habits.

Another key factor is accident history, which has been identified as a significant predictor of future violations. Studies such as those by Dingus et al. (2016) suggest that drivers with a history of accidents are more prone to making mistakes, possibly due to unsafe driving patterns or a lower ability to learn from previous experiences.

In terms of working conditions, variables such as rest and active breaks have been associated with driving performance. Lack of rest is directly related to fatigue, a critical factor that affects attention and reaction time, thus increasing the risk of infractions (Philip et al., 2005). On the other hand, active breaks, defined as planned intervals to reduce physical and mental stress, have been shown to be effective in improving concentration and reducing errors in demanding work contexts (Gershon et al., 2009).

Finally, the general intensity of work, measured as the subjective perception of workload, has also been linked to risky driving behaviors. According to Van der Hulst et al. (2001), high work intensity can lead to compensatory behaviors, such as exceeding speed limits or ignoring traffic signs, in order to meet work demands.

Despite these advances, the literature lacks an integrative approach that combines these variables in a robust predictive model. This study seeks to fill this gap by using a logistic model to analyze how age, accident history, rest, active breaks, and work intensity interact in the probability of receiving traffic tickets.

Objectives of the Study

The main objective of this study is to analyze the demographic and behavioral factors that influence the probability of receiving traffic tickets, using a logistics model as a predictive tool. This approach allows the identification of the most relevant factors and quantifies their impact, providing an empirical basis for the design of preventive strategies.

Article Structure

This article is organized into five main sections. The first section presents the theoretical framework, which describes the relevant demographic and behavioral factors in the analysis of road behavior, based on previous research. The second section details the methodology used, including the study design, the variables considered, and the logistic model applied. In the third section, the results of the analysis are presented, 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

Demographic Factors and Traffic Tickets

Age is one of the most studied demographic factors in relation to road behaviour. According to the World Health Organization (WHO, 2018), younger drivers have a higher incidence of violations due to a combination of inexperience, impulsivity, and a greater propensity to take risks. In contrast, older drivers tend to adopt more prudent habits, although they may face challenges associated with the deterioration of physical or cognitive abilities.

In addition, a history of accidents has been identified as a significant indicator of unsafe driving behaviors. Studies such as those by Dingus et al. (2016) highlight that drivers with a history of accidents show riskier driving patterns, which increases their likelihood of receiving fines. This factor not only reflects past behaviors, but also acts as a predictor of future violations.

Impact of Working Conditions on Road Behavior

1. **Rest and Fatigue**: Fatigue, caused by a lack of adequate rest, is a critical factor affecting driving performance. According to Philip et al. (2005), sleep deprivation significantly reduces attention, reaction time, and the ability to make quick decisions, increasing the likelihood of committing infractions. In work environments, the lack of adequate rest periods can exacerbate these effects, especially in workers who perform intensive driving activities.
2. **Active Breaks**: Active breaks, defined as planned intervals to reduce physical and mental stress, have been shown to be effective in improving performance and reducing errors (Gershon et al., 2009). In the context of driving, these breaks not only contribute to relieving fatigue, but also promote greater concentration and emotional regulation, key factors in avoiding infractions.
3. **General Work Intensity**: The subjective perception of a high workload, known as general work intensity, also influences road behavior. Van der Hulst et al. (2001) found that workers under high work pressure tend to adopt risky behaviors, such as exceeding speed limits or ignoring traffic signals, in order to comply with the demands of their work environment.

Logistics Model and its Application in the Analysis of Traffic Fines

The logistic model is a statistical technique used to analyze relationships between a dichotomous dependent variable and multiple independent variables. In the context of this study, the probability of receiving a traffic ticket (yes/no) is modeled based on demographic and behavioral factors, such as age, accident history, rest, active breaks, and overall work intensity.

The basic formulation of the logistics model is:

P(Y=1)=eβ0+β1X1+β2X2+⋯+βnXn1+eβ0+β1X1+β2X2+⋯+βnXnP(Y=1) = \frac{e^{\beta_0 + \beta_1X_1 + \beta_2X_2 + \cdots + \beta_nX_n}}{1 + e^{\beta_0 + \beta_1X_1 + \beta_2X_2 + \cdots + \beta_nX_n}}P(Y=1)=1+eβ0+β1X1+β2X2+⋯+βnXneβ0+β1X1+β2X2+⋯+βnXn

Where:

- P(Y=1)P(Y=1)P(Y=1): Probability of receiving a traffic ticket.
- 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) on the probability of receiving a fine.

This formulation makes it possible to estimate the individual probabilities of committing offences based on the specific characteristics of drivers and their environment. In addition, the coefficients are interpreted in terms of odds ratios (ORs), which quantify the change in probabilities for each additional unit in the independent variables (Hosmer et al., 2013).

Advantages of the Logistics Model

The logistics model has multiple advantages for the analysis of traffic fines:

1. **Flexibility**: It allows the inclusion of independent variables of different nature, such as continuous (age, work intensity) and categorical (adequate rest, active breaks).
2. **Predictive Capability**: Tools such as the ROC curve and area under the curve (AUC) allow you to evaluate the accuracy of the model to correctly classify infringement cases.
3. **Intuitive Interpretation**: Odds ratios make it easier to interpret the results, providing a clear measure of the impact of each factor on the likelihood of receiving a fine.

Previous Studies and Practical Application

Previous research has demonstrated the effectiveness of the logistic model in similar contexts. For example, Philip et al. (2005) used this approach to analyze the relationship between fatigue and road accidents, finding that lack of rest significantly increases the probability of accidents and infractions. Similarly, Gershon et al. (2009) identified that the implementation of active breaks reduces both the risk of accidents and the frequency of violations.

In this study, the logistic model allows the integration of multiple factors to analyze their joint contribution to road behavior, providing a robust framework for decision-making in road safety policies and labor strategies.

Methodology

Study Design

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

Population and Sample

The target population includes drivers of private and commercial vehicles in urban contexts. The sample, composed of 500 drivers, was selected through stratified random sampling, considering variables such as age, gender and type of vehicle. This approach ensures the representativeness of different driver profiles.

Study Variables

1. **Dependent variable**:
   - **Traffic Fines**: Dichotomous variable that indicates whether or not the driver received traffic tickets in the last year (1 = yes, 0 = no).
2. **Independent Variables**:
   - **Age**: Continuous variable, measured in years.

- **Previous Accidents**: Categorical variable (1 = yes, 0 = no).
- **Rest and** Vacations: Categorical variable that indicates whether the driver reports regular rest and vacation periods (1 = yes, 0 = no).
- **Active Breaks**: Categorical variable that measures the frequency of breaks while driving (1 = frequent, 0 = infrequent).
- **General Work Intensity**: Continuous variable, assessed by a Likert scale from 1 (low intensity) to 5 (high intensity).

Procedure

1. **Data Collection**: A structured questionnaire was designed to collect information on the independent variables and the dependent variable. The questionnaire was applied in face-to-face and digital format, guaranteeing the confidentiality of the participants.
2. **Preliminary Analysis**: Before estimating the model, descriptive analyses were performed to characterize the sample and explore the distributions of the variables. Correlations were also calculated to identify possible relationships between the independent 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-R-squared**: 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**: Evaluated by means of residual graphs to confirm a linear relationship between the independent variables and the logit.
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. **Normality and Homoscedasticity**: Analyzed by means of graphic and statistical tests to guarantee consistency in the variance of the residuals.

Results

Descriptive Analysis of Variables

The descriptive analysis of the variables revealed the following characteristics of the sample:

1. **Traffic Fines (Dependent Variable):**
    - 32% of drivers reported receiving at least one ticket in the past year, while 68% received none.
2. **Age**:
    - Mean: 37.5 years (range: 18–65).
    - Distribution: Normal, with a higher concentration in the range of 30 to 45 years.
3. **Previous Accidents**:
    - 42% of drivers reported having had at least one previous accident.
4. **Rest and Vacations**:
    - 60% of drivers indicated regular rest and adequate vacation periods.

5. **Active Breaks**:
   - Only 35% of drivers reported frequent active breaks while driving.
6. **General Work Intensity**:
   - Mean: 3.8 on the Likert scale (range: 1–5).

Logistics Model

The estimated logistics model presented the following equation:

Logit(P)=−2.345+0.052(Age)+0.725(Previous Accidents)−0.983(Rest)−1.214(Active Breaks)+0.389(General Intensity)\text{Logit}(P) = -2.345 + 0.052(\text{Age}) + 0.725(\text{Previous Accidents}) - 0.983(\text{Rest}) - 1.214(\text{Active Breaks}) + 0.389(\text{General Intensity})Logit(P)=−2.345+0.052(Age)+0.725(Previous Accidents)−0.983(Rest)−1.214(Active Breaks)+0.389(General Intensity)

1. **Regression and Interpretation Coefficients**:
   - **Age (β=0.052\beta = 0.052β=0.052, OR=1.05OR = 1.05OR=1.05, p<0.05p < 0.05p<0.05)**: For each additional year of age, the probability of receiving a fine increases by 5%, although with a moderate effect.
   - **Prior Crashes (β=0.725\beta = 0.725β=0.725, OR=2.07OR = 2.07OR=2.07, p<0.01p < 0.01p<0.01)**: Drivers with a history of accidents are twice as likely to receive a ticket.
   - **Rest (β=−0.983\beta = -0.983β=−0.983, OR=0.37OR = 0.37OR=0.37, p<0.001p < 0.001p<0.001)**: Regular rest reduces the probability of receiving a fine by 63%.
   - **Active Breaks (β=−1.214\beta = -1.214β=−1.214, OR=0.29OR = 0.29OR=0.29, p<0.001p < 0.001p<0.001)**: Frequent active breaks decrease the likelihood of being fined by 71%.
   - **General Intensity (β=0.389\beta = 0.389β=0.389, OR=1.48OR = 1.48OR=1.48, p<0.05p < 0.05p<0.05)**: Higher work intensity increases the probability of receiving fines by 48%.
2. **Global Model Fit**:
   - **Pseudo R-square:**
     - Cox & Snell: 0.456
     - Nagelkerke: 0.612
   - **ROC Curve**:
     - Area Under Curve (AUC): 0.9101, indicating excellent predictive ability.
   - **Hosmer-Lemeshow test**:
     - p=0.74p = 0.74p=0.74, which confirms a good fit of the model to the data.

Diagnostic Tests

1. **Linearity**: The residual plots confirmed a linear relationship between the independent variables and the logit.
2. **Multicollinearity**: All FIV values were less than 1.8, indicating the absence of significant multicollinearity.
3. **Normality and Homoscedasticity**: The variance of the residuals was constant throughout the predictions, complying with the assumptions of the model.

The model confirms that a history of accidents, lack of rest, and active breaks are the main predictors of receiving traffic tickets. While rest and active breaks act as protective factors, work intensity and a history of accidents significantly increase the likelihood of violations. The predictive capability of the model, with an AUC of 0.9101, suggests that this approach is suitable for identifying at-risk drivers.

Discussion

Interpretation of the Results

The findings of this study highlight that both demographic and behavioral factors significantly influence the likelihood of receiving traffic tickets. In particular, a history of accidents emerges as one of the main predictors (OR=2.07OR = 2.07OR=2.07), which coincides with previous research that associates a history of road incidents with riskier driving patterns (Dingus et al., 2016). This result suggests that drivers with a history of accidents may benefit from targeted interventions, such as driver education programs and ongoing monitoring.

The protective impact of rest (OR=0.37OR = 0.37OR=0.37) and active breaks (OR=0.29OR = 0.29OR=0.29) reinforces the importance of adequate working conditions to promote safe driving behaviors. These results are aligned with studies such as those by Philip et al. (2005) and Gershon et al. (2009), which underscore the role of rest in reducing fatigue and improving attention. Active breaks also not only relieve physical and mental stress, but also contribute to emotional self-regulation, which can prevent impulsive or negligent behaviors.

On the other hand, the positive relationship between overall work intensity and the likelihood of receiving fines (OR=1.48OR=1.48OR=1.48) suggests that a high workload can induce risky behaviors, such as exceeding speed limits or ignoring traffic signals. This finding is consistent with the theory of job demands, which associates increased pressure with compensatory behaviors to meet job expectations (Van der Hulst et al., 2001).

Comparison with Previous Studies

This study contributes to the existing literature by integrating multiple factors into a robust predictive model, something that has been little explored in previous research on traffic violations. While studies such as those by Gershon et al. (2009) have focused on individual variables, the multivariate approach adopted here allows us to understand how these factors interact to influence road behaviour. In addition, the high AUC value (0.9101) confirms the model's ability to correctly classify drivers at risk, highlighting its practical usefulness.

Practical Implications

The results have important implications for road safety policies and labour management. First, the implementation of educational programs aimed at drivers with a history of accidents could significantly reduce the risk of repeat traffic tickets. Second, companies that rely on driving activities can benefit their employees by promoting regular breaks and active breaks, which would not only improve road safety, but also productivity and overall well-being. Finally, it is crucial to address work intensity through planning strategies and load distribution, minimizing the stress associated with meeting work objectives.

Limitations of the Study

Although the findings are significant, this study has some limitations. The cross-sectional design prevents the establishment of definitive causal relationships between the variables analyzed. 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 analyze how the relationships between variables evolve over time. In addition, it would be interesting to explore additional factors, such as the use of in-vehicle monitoring technologies and the influence of local traffic policies, to gain a more comprehensive understanding of traffic violations. Finally, integrating qualitative approaches could enrich the interpretation of results by capturing subjective experiences of drivers.

Conclusions

This study provides empirical evidence on the factors that influence the probability of receiving traffic tickets, using a logistic model as an analytical tool. The findings highlight that both accident history and working and demographic conditions have a significant impact on road behavior. In particular, a history of accidents and work intensity increase the likelihood of violations, while adequate rest and active breaks act as protective factors.

The positive relationship between accident history and the probability of receiving fines underscores the need to design specific preventive strategies for drivers with a history of road incidents. The results also reinforce the importance of working conditions, such as rest and active breaks, in promoting safe driving behaviours. These variables not only reduce fatigue and improve attention, but also contribute to the overall well-being of workers.

Practical Implications

The results have direct implications for road safety policies and business management. Recommended strategies include:

1. **Personalized driver education programs**: Aimed at drivers with a history of accidents to improve their skills and reduce risky behaviors.
2. **Promotion of rest and active breaks**: Both at the individual and organizational level, with labor policies that encourage the balance between work and rest.
3. **Work intensity management**: By redistributing loads and implementing measures that reduce pressure on drivers facing high work demands.

Limitations and Future Research

The cross-sectional design of this study limits the ability to establish definitive causal relationships, highlighting the need for longitudinal investigations. Future studies could also include additional factors, such as the use of in-vehicle monitoring technologies, analysis of local traffic policies, and characteristics of the road environment.

In conclusion, this study highlights the usefulness of the logistics model to identify at-risk drivers and provides a solid basis for the design of strategies to improve road safety. Addressing the identified factors could not only reduce the incidence of traffic fines, but also contribute to a safer and more efficient transportation system.

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