Eco-Driving Effectiveness in Reducing Emissions and Crashes in Rural Areas

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Abstract

The increasing challenges of road safety and environmental sustainability necessitate effective driving strategies. Eco-driving has emerged as a promising approach to reducing pollutant emissions and mitigating crash risks. This study explores the impact of eco-driving in rural and mountainous areas through an experimental methodology using a driving simulator. A total of 39 participants were assessed across multiple driving scenarios before and after receiving eco-driving training, while their demographic, behavioral, and driving-related characteristics were systematically collected and analyzed through a questionnaire survey. Each individual completed two driving sessions per scenario: one under regular driving conditions and another following eco-driving training guidelines. To evaluate the influence of eco-driving on fuel consumption, crash probability, and pollutant emissions (CO_2, CO, and NO_x), linear and logistic regression models were applied. The results indicate that adopting eco-driving practices leads to significant reductions in emissions, fuel consumption, and crash probability.

Keywords: *eco-driving, driving simulator, rural environment, pollutant environmental emissions, fuel consumption, road safety, statistical modeling*

1. Introduction

Road transport emissions represent a significant global challenge, contributing to both deteriorating air quality and climate change. The combustion of fuels in vehicles generates harmful environmental pollutants, such as nitrogen oxides (NOx), carbon dioxide (CO_2), and carbon monoxide (CO), all of which contribute to poor air quality and climate change. The European Environment Agency (EEA) reported that in 2020 alone, exposure to fine particulate matter (PM2.5) led to at least 238,000 premature deaths in the European Union. This demonstrates the urgent need for cleaner, more sustainable transportation practices (European Environment Agency, 2022). Recent studies underscore the disproportionate impact of transport emissions on vulnerable urban populations, where air pollutants such as particulate matter and nitrogen dioxide exacerbate respiratory and cardiovascular diseases, contributing to increased morbidity and mortality (Nieuwenhuijsen, 2018). Furthermore, studies indicate that these health impacts are particularly severe in densely populated urban centers, necessitating tailored policy responses that prioritize low-emission technologies and behavioral interventions (Huang et al., 2021).

Studies show that eco-driving can reduce emissions by 5% to 40%, depending on the driving conditions and the driver's compliance to eco-driving principles. For instance, a study by Morello et al. (2016) found that eco-driving could lead to a 15% reduction in CO_2 emissions during free-flowing traffic, with diminishing effects during congested conditions. Another study by Arroyo-López et al. (2022) reported that eco-driving could reduce CO_2 emissions by an average of 13 kg per trip. Additional evidence suggests that pairing eco-driving training with in-vehicle technologies, such as adaptive cruise control and eco-assist systems, can further optimize fuel consumption and emissions reductions (Ng et al., 2021). Recent studies by Huang et al. (2021) confirm that integrating eco-driving with telematics and real-time feedback systems can reduce NOx emissions by up to 65% and fuel consumption by 6%, especially among inexperienced drivers. Similarly, Wang & Boggio-Marzet (2018) demonstrated that eco-driving programs tailored to specific road types yield sustained fuel savings of up to 6.3%, reinforcing the importance of adaptive training methods. The aforementioned findings are verified by Ayyildiz et al. (2017) who further highlight that eco-driving interventions can lower heavy vehicle fuel consumption by 5.5%, providing strong evidence for its scalability across transportation sectors.

The benefits of eco-driving are not limited to environmental outcomes. It also enhances road safety by encouraging less aggressive driving behaviors, leading to lower crash rates. Research by Jamson et al. (2015) demonstrated that eco-driving could reduce abrupt pedal movements, leading to smoother driving behavior and, ultimately, fewer road crashes. Moreover, a study by Nævestad (2022) showed that companies implementing eco-driving measures reduced their crash risk by up to 52% for heavy vehicles, a significant reduction that highlights the potential of eco-driving in improving road safety. According to the WHO (World Health Organization, 2023), road traffic crashes are a leading cause of death for children and young people aged 5–29 years, claiming approximately 1.19 million lives each year and leaving many more people injured. This high toll of fatalities and injuries reflects the need for better preventive strategies, including behavioral approaches such as eco-driving, that can complement existing technological and infrastructural solutions. Further reinforcing this perspective, Li et al. (2019) demonstrated that in-vehicle eco-safe driving systems not only improve driver attentiveness but also enhance visual focus without causing distraction, thereby supporting safer driving practices. Moreover, Ma et al. (2021) highlighted the energy and safety benefits of eco-driving-based cooperative adaptive cruise control (Eco-CACC), which reduces energy consumption by 8.02% and improves safety during vehicle platooning at intersections. Additionally, recent findings by Huang et al. (2018) emphasize that such technologies, when integrated with eco-driving principles, can deliver sustained benefits even in mixed-traffic environments where driver behavior may vary significantly.

Considering the literature findings, this study is essential for addressing the dual challenge of reducing emissions and improving road safety by exploring the impacts of eco-driving. Furthermore, rural environments, which remain underexplored in previous studies, will be investigated using a driving simulator. The unique contribution of this research lies in its ability to quantify the environmental and safety benefits of eco-driving through a controlled, experimental framework by analyzing the effects of eco-driving on pollutant emissions and crash probability. This study provides valuable insights that could inform future transportation policies and driver education programs globally.

This study is structured as follows: First, after an overview of the field of eco-driving and road safety research, a detailed description of the research methodology is provided, including the theoretical basis of the models, as well as the experimental framework, data collection and processing procedures. Results are presented to quantify eco-driving effects on emissions and crash probabilities, concluding in practical recommendations for integrating eco-driving principles into transportation systems.

2. *Methodology*

2.1 Experiment Overview

2.1.1 Simulator Experiment

In order to assess the impact of eco-driving techniques on both pollutant emissions and road safety, data were collected using a driving simulator at the Department of Transportation Planning and Engineering of the National Technical University of Athens (NTUA). Specifically, the study utilized a FOERST Driving Simulator FP (Fig. 1), which includes three wide Full HD LCD screens, a driving seat, and a motion-support base. The simulator measures 230 x 180 cm, with a base width of 78 cm and provides a total field of view of 170 degrees.

Figure 1: *NTUA FOERST Driving Simulator*

The digital environment provides a realistic visualization of the road network from the driver's perspective, allowing full control through the use of mirrors. It offers the flexibility to simulate various driving conditions, including different road types (urban, rural, highway), traffic levels (normal, heavy), lighting settings (day, night, fog), and weather conditions (clear, rain, snow). Additionally, the simulation incorporates random events such as pedestrian crossings, unexpected behavior from other vehicles, and sudden obstacles, enabling the study of driver responses under challenging scenarios. The driving simulator captures approximately 60 measurements per second throughout the experiments, with the data exported as a text file. Each driving scenario generates its own file, containing values for multiple variables that are critical to the analysis. These variables, along with their descriptions, are presented in Table 1.

Table 1: *Driving Simulator Variables*

Variable	Explanation
Time	Current real-time in milliseconds since start of the drive.
x-pos	x-position of vehicle in m.
y-pos	y-position of vehicle in m.
z-pos	z-position of vehicle in m
Road	Road number of the vehicle in [int].
Richt	Direction of the vehicle on the road in [BOOL] (0/1).
Rdist	Distance of the vehicle from the beginning of the drive-in m.
rspur	Track of the vehicle from the middle of the road in m.
ralpha	Direction of the vehicle compared to the road direction in degrees.
Dist	Driven course in meters since begin of the drive.
Speed	Actual speed in km/h.
Brk	Brake pedal position in percent.
Acc	Gas pedal position in percent.
Clutch	Clutch pedal position in percent.
Gear	Chosen gear (0 = idle, 6 = reverse).
RPM	Motor revolvation in 1/min.
HWay	Headway, distance to the ahead driving vehicle in m.
DLeft	Distance to the left road board in m.
DRicht	Distance to the right road board in m.
Wheel	Steering wheel position in degrees.
Thead	Time to headway, i.e., to collision with the ahead driving vehicle in ms.
TTL	Time to line crossing, time until the road border line is exceeded, in ms.
TTC	Time to collision (all obstacles), in ms.

2.1.2 Experiment Scenarios

For the purposes of this study, as previously outlined, the experiment was conducted on two network types: rural network (**Figure 2**) and mountainous rural network (**Figure 3**). The network features a specific track that provides one (1) lane per direction for the mountainous rural network and one (1) lane per direction for the rural network. The road network also included appropriate traffic signage, such as speed limits, sharp turns, and animal warnings about the presence of wildlife. In each scenario, two hazardous events were introduced - either a wild animal (e.g., a wild deer) crossing. These events were randomly positioned in each scenario to avoid learning effects. The selected traffic volume characteristics for the single lane per direction included a low traffic volume of 300 vehicles per hour. Vehicle arrivals followed a Gamma distribution with a mean of m = 12 seconds and a variance of σ^2 = 6 seconds^2.

Figure 2: *Rural driving simulator environment*

Figure 3: *Mountainous rural driving simulator environment*

2.1.3 Experiment Implementation

To conduct the within driving experiment, young drivers with valid licenses were voluntarily selected from two age groups: 18-23 years and 24-30 years, to examine driving behavior based on driver experience. Gender balance was also considered in the selection process. A total of 39 drivers participated, including 23 men and 16 women, with an average of 4 years of driving experience. The participants were distributed by age group, with 56% in the 18-23 range and 44% in the 24-30 range, while gender distribution was 59% male and 41% female.

The experiment began with a familiarization phase of around 5 minutes, allowing drivers to get accustomed to the simulator and finalize the settings. The phase was extended where suitable. To introduce randomness into the sample, each participant drove the scenarios (i.e., rural and mountainous rural route) twice, but in a different order (i.e., each driver completed four driving sessions). Additionally, a questionnaire was created to assess the driver's profile, with a focus on their eco-driving behavior. The experiment was divided into two phases.

- ***Phase 1****: In the initial stage of this phase, participants completed a test drive to familiarize themselves with the simulator. After the practice session, the 39 participants proceeded to drive two main scenarios in the simulator.*
- ***Phase 2****: Before beginning this phase, participants answered a questionnaire to determine their driving profile. They were then given information on eco-driving techniques. In the second phase, participants repeated the exact same driving scenarios as in Phase 1, but this time they applied eco-driving techniques based informational leaflet they had received.*

As stated previously, prior to the second phase, each participant received individual instructions on eco-driving. An informational leaflet on eco-driving was developed to inform the drivers. This brochure included key instructions for practicing eco-driving, which were read by the drivers, such as:

- *Speed limits should be adhered to, with an emphasis on driving at reduced speeds.*
- *Efforts should be made to maintain a steady speed whenever feasible.*
- *Synchronization with the speed of surrounding vehicles should be prioritized.*
- *Engine revolutions should be kept below 2000 RPM.*
- *Maximum coasting should be achieved without engaging the accelerator.*
- *Abrupt accelerations should be avoided by initiating gradual movement.*
- *Sudden braking should be minimized by anticipating and responding to braking needs in advance.*
- *Sharp changes in speed should be avoided by maintaining adequate distance from other vehicles.*
- *Unnecessary acceleration on downhill slopes should be avoided.*
- *Sufficient momentum should be gathered to facilitate uphill ascents.*

The Phase 2 questionnaire comprised 31 items covering four domains - driving experience, vehicle characteristics, eco-driving behaviors, and attitudes toward eco-driving. Responses were coded into corresponding variables, yielding a 39 × 31 data matrix that underpinned the subsequent analyses of driving behaviour, environmental impact, and safety outcomes.

2.1.4 Emission and Fuel Consumption Calculation

After the data collection, additional indicators related to emissions and fuel consumption were calculated, which were not directly provided by the simulator. Indicators such as VSP, CO_2, CO, HC, NOx, FC were calculated based on certain indications from previous studies (Zhao et al., 2015).

First, the Vehicle Specific Power (VSP) index was calculated, representing a microscopic emissions model based on the distribution of vehicle-specific power. It is computed using the vehicle's speed and acceleration per second, following the equation (**Eq. 1**) below:

$$\text{VSP} = \frac{0{,}156461 \times u + 0{,}00200193 \times u^2 + 0{,}000492646 \times u^3 + 1{,}4788 \times u \times \alpha}{1{,}4788}, \quad \textbf{(1)}$$

Where u: vehicle speed (m/s); a: vehicle acceleration (m/s^2)

Subsequently, the other indicators – CO_2 (carbon dioxide), CO (carbon monoxide), HC (hydrocarbons), and NOx (nitrogen oxides) - were calculated based on **Table 2**, which correlates the VSP values (in grams per second) with these specific pollutants.

Table 2: *Base emission rate in VSP bins (g/s) (Zhao et al., 2015)*

VSP bins	CO_2	CO	HC	NOx
<0	1.632545455	0.00217615	0.000438919	0.000073716
0	0.568829787	0.00110017	0.000135847	0.000007291
(0,1]	1.255982829	0.003240577	0.000254022	0.00012592
(1,2]	1.849368682	0.003378486	0.000299352	0.000183509
(2,3]	2.306617803	0.003476258	0.000352772	0.000181848
(3,4]	2.384342143	0.003559317	0.000415724	0.000174986
(4,5]	2.416571296	0.003653089	0.00048991	0.000165734
(5,6]	3.501662832	0.003782998	0.000577334	0.000188866
(6,7]	3.491228867	0.00397447	0.000680359	0.000227813
(7,8]	4.543236125	0.00425293	0.000801769	0.000298345
(8,9]	4.678231939	0.004643802	0.000944845	0.000476234
(9,10]	5.053493392	0.005172511	0.001113453	0.000537252
(10,11]	4.339905443	0.005864483	0.001312148	0.00058717
(11,12]	4.78196911	0.006745142	0.001421257	0.000686759
(12,13]	5.8109181	0.007839914	0.001444166	0.000896791
(13,14]	5.2327381	0.010074223	0.001504755	0.001158038
(14,15]	5.4149725	0.010773495	0.001561731	0.00120127
(15,16]	6.2459078	0.013563155	0.001615094	0.001417259
(16,17]	6.0417608	0.014868627	0.001672916	0.001446777
(17,18]	6.3793126	0.017415336	0.00177098	0.001620595
(18,19]	6.2072115	0.020328708	0.001783503	0.001909484
(19,20]	6.8681762	0.023634167	0.002024126	0.001924216
(20,21]	7.3175052	0.027357139	0.001870938	0.002265563
(21,22]	7.6165789	0.031523048	0.00209393	0.002334295
(22,23]	7.8234731	0.03465732	0.002074634	0.002431184
(23,24]	8.0016609	0.03828538	0.002211921	0.002857002
>24	8.3430313	0.040932652	0.002232765	0.00271252

Lastly, the Fuel Consumption (FC) indicator was calculated using the carbon balance method, which applies an equation (**Eq. 2**) that integrates emissions per kilometer with the distance traveled by the vehicle, as reported in Zhao et al. (2015).

$$FC = (0.866 \times M_{HC} + 0.4286 \times M_{CO} + 0.2727 \times M_{CO2}) \times 0.156, \quad \textbf{(2)}$$

Where:

- *M_{HC}: HC emissions (g/km)*
- *M_{CO}: CO emissions (g/km)*
- *M_{CO2}: CO2 emissions (g/km)*

Then all three datasets (driving simulator variables, questionnaire, and environmental variables) were aggregated by participant and scenario comprised the data collected from the simulator, the participants' questionnaire responses, and the calculated environmental indicators. The final dataset had dimensions of 313x112.

2.2 Model Development

The key objective of this research is to develop mathematical. These models aimed to measure the impact of eco-driving on important outcomes such as fuel consumption, pollutant emissions, and crash probability. This technique assures that the models are not only statistically accurate, but also practically useful, by combining theoretical and empirical consistency. To effectively capture the complex dynamics of eco-driving, the models developed utilizing regression methods and statistical requirements.

2.2.1 Linear Regression

Linear regression was employed to quantify the relationships between eco-driving behaviors and continuous dependent variables, such as fuel consumption and pollutant emissions. This relationship is mathematically represented as (**Eq. 3**):

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni} + \varepsilon_i, \quad \textbf{(3)}$$

Where:

- *Y_i represents the dependent variable*
- *$X_1, X_2, \ldots, X_n$ representing the independent variables.*
- *β_0 represents the intercept.*
- *ε_i is the residual error term.*

2.2.2 Binary Logistic Regression Model

For categorical outcomes, particularly those concerning the probability of a crash occurring, the binary logistic regression model was employed. This model is particularly suited for binary outcomes where the dependent variable Y_i takes on one of two values, typically coded as 1 for success and 0 for failure. The logistic regression model predicts the log odds of the dependent variable as a linear function of the independent variables (**Eq. 4**). This relationship is expressed as:

$$Y_i = \ln\frac{P_i}{1 - P_i} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_n X_{ni}, \quad \textbf{(4)}$$

Where:

- *Y_i represents the dependent variable, which is assigned value 1 with probability of success P and value 0 with probability of failure 1-P.*
- *$X_1, X_2, \ldots, X_n$ representing the independent variables.*
- *β_0 represents the intercept.*
- *P_i is the predicted probability, which is set to values of 0 (failure) and 1 (success).*

2.2.3 Acceptance Criteria and Result Interpretation

The validation of mathematical models necessitates a consistent evaluation framework to ensure statistical robustness, theoretical consistency, and predictive efficacy. Statistical significance is assessed using p values for linear models and logistic models.

Model quality is quantified through the coefficient of determination (R^2) for linear models, where values approaching unity signify superior explanatory power and predictive accuracy. The R^2 is calculated as (**Eq. 5**):

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\widehat{Y_i} - \overline{Y})^2}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2} = 1 - \frac{\sum_{i=1}^{n}(Y_i - \widehat{Y_i})^2}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}, \quad \textbf{(5)}$$

Where:

- *$\widehat{Y_i}$ represents the model's predicted independent variable.*
- *$\overline{Y}$ represents the mean value of the independent variable Yi.*

R^2 ranges from 0 to 1, with the closer the value of R^2 to 1, the stronger the linear dependence relationship between variables Y and X becomes (i.e., more accurate predictions). Logistic models are evaluated based on predictive classification accuracy, with thresholds exceeding 65% deemed satisfactory.

The elasticity of the independent variables was also computed to assess the responsiveness and sensitivity of the dependent variable to changes in each independent variable (Washington et al., 2011). This calculation enabled a comparison of the impacts of the various independent variables on the dependent variable. Additionally, the elasticity (e_i^*) for each variable was determined by dividing the elasticity of each variable by that of the variable with the smallest impact on the dependent variable.

Elasticity for continuous predictors is given by (**Eq. 6**):

$e_i = \left(\frac{\Delta Y_\iota}{\Delta X_\iota}\right)\left(\frac{X_\iota}{Y_\iota}\right)$, **(6)**

For discrete (categorical) predictors, pseudo-elasticity offers an analogous metric, capturing shifts resulting from categorical transitions. Mathematical equations are distinguished between discrete variables (Eq. 7) and continuous variables (Eq. 8):

$$E_{x_{ink}}^{P_i} = e^{\beta_{ik}} \frac{\sum_{i=1}^{I} e^{\beta i x_n}}{\sum_{i=1}^{I} e^{\Delta(\beta i x_n)}} - 1, \quad (7)$$

$$E_{x_{ink}}^{P_i} = [1 - \sum_{i=1}^{I} P_n(i)]\, x_{ink}\beta_{ik}, \quad (8)$$

Where:

- *i represents the number of possible options.*
- *P_i denotes the probability of alternative i.*
- *x_{ink} indicates the value of variable k for alternative i of individual n.*
- *$\Delta(\beta_i x_n)$ defines the value of the function that determines each option after the value of x_{ink} has changed from 0 to 1.*
- *$\beta_i x_n$ represents the corresponding value when x_{nk} is 0.*
- *β_{ik} specifies the parameter value of variable x_{nk}.*

3. *Results*

3.1 CO_2 Emissions

This section further presents the CO_2 emissions linear regression model, starting with the regression equation, followed by the table with regression exports extracted using R language. This regression model demonstrates that carbon dioxide (CO_2) emissions exhibit a strong dependence on ecological driving behaviors, underscoring the efficacy of eco-driving strategies. The empirical findings indicate a substantial reduction of 5.9% or 19.45 g/km in CO_2 emissions attributable to eco-driving practices. Rural driving environments, characterized by flatter terrain and fewer abrupt changes in elevation, were associated with lower emissions compared to mountainous rural terrains, where frequent acceleration and deceleration are necessitated. Conversely, elevated braking intensity and increased lateral acceleration emerged as key contributors to heightened emissions, emphasizing the impact of abrupt maneuvers. The mathematical equation for the regression model of CO_2 emissions is given by (**Eq. 9**):

y (CO_2/km) = 309.057 – 19.45×(Eco) – 40.306×(Environment) - 2.036×(RoutesPerDay) + 6.648×(AvgBrk) – 19.485×(AvgDLeft) + 8.583×(StdAccLat), **(9)**

Where:

- ***CO_2/km**: CO_2 emissions per kilometer driven (g/km).*
- ***Eco**: Eco-driving scenario (e.g., 0 = Non-eco driving behavior and 1 = Eco-driving behavior)*
- ***Environment**: Driving environment (e.g., 0 = Mountainous rural network, 1 = Rural network).*
- ***RoutesPerDay**: Average number of trips per day (e.g., 0 = 0 trips, 1 = 1 trip, ..., 6 = more than 5 trips).*
- ***AvgBrk**: Average brake-pedal usage (%) during driving.*
- ***AvgDLeft**: Average distance from the left side of the road (m).*
- ***StdAccLat**: Standard deviation of lateral acceleration (m/s^2).*

Table 3 displays the regression coefficients and associated statistics for each variable in the model. With regard to the model's statistical significance, it is noted that all t-test values for each variable exceed 1.7, and all p-values are below 0.05. This indicates that each variable's effect is statistically significant at the 95% confidence level. In addition, to measure each independent variable impact on CO_2 emissions, both elasticity (e) and relative elasticity (e*) are calculated. The latter (e*) for each variable was determined by dividing the elasticity of each variable by that of the variable with the smallest impact on the dependent variable. From Table 3, Environment has the strongest effect on CO_2/km, at 19.80 times the smallest influence (RoutesPerDay). Likewise, eco-driving outweighs the smallest effect by a factor of 9.5. Among continuous variables, AvgDLeft shows the highest influence 2.93 times the smallest (AvgBrk). Finally, StdAccLat is 1.3 times greater than the lowest influence.

Table 3: Model of CO^2/km Prediction

Independent Variables	βi	Std. Error	t Value	p-Value	e	e*
(Constant)	309.057	7.533	41.028	0.000 ***		
Discrete variables						
Eco	-19.450	3.274	-5.940	0.000 ***	-0.059	9.55
Environment	-40.306	3.309	-12.181	0.000 ***	-0.121	19.80
RoutesPerDay	-2.036	0.970	-2.099	0.038 *	-0.006	1.00
Continuous variables						
AvgBrk	6.648	0.471	14.124	0.000 ***	0.0002	1.00
AvgDLeft	-19.485	7.370	-2.644	0.009 **	0.0006	2.93
StdAccLat	8.583	2.580	3.326	0.001 **	0.0003	1.29
R^2 = 0.836						
Adjusted R^2 = 0.830						

* Significance at the 90% confidence level/**95%/*** 99.9%.

The regression analysis reveals that eco-driving results in a 5.9% reduction in emissions. This finding highlights the effectiveness of smoother accelerations, lower speeds, and reduced engine revolutions (RPM) in cutting emissions. Moreover, driving in rural environments further reduces emissions compared to mountainous rural terrains, where frequent braking and acceleration are required; this is supported by an elasticity of e=−0.121, indicating a 12.1% decrease in emissions when transitioning from mountainous to rural terrain. In addition, the average number of trips per day (RoutesPerDay) exhibits the smallest elasticity (e=−0.006), suggesting that frequent driving might help drivers develop efficient habits that slightly lower emissions. Furthermore, increased brake usage (AvgBrk) leads to higher emissions, as energy losses from braking necessitate additional engine power and this is reflected in a positive elasticity of e=0.0002. On the other hand, a greater average distance from the left side of the road (AvgDLeft) reduces emissions (e=0.0006). This suggests that drivers who position themselves further to the right tend to adopt a more defensive driving style, avoiding aggressive behaviors like overtaking. As a result, their cautious approach likely contributes to lower fuel consumption. Lastly, increased variability in lateral acceleration (StdAccLat) raises emissions, as unstable driving patterns like sharp turns disrupt steady motion, shown by a positive elasticity of e=0.0003. Overall, with an R^2 value of 0.836, the model explains 83.6% of the variance in emissions, confirming the substantial impact of eco-driving behaviors, terrain, and steady driving patterns in mitigating CO_2 emissions.

3.2 CO Emissions

The model evaluating carbon monoxide (CO) emissions further validates the impact of ecological driving practices. Results revealed a 29.3% or 0.219 g/km reduction in emissions under eco-driving conditions. However, high variability in braking patterns was shown to worsen CO emissions, indicating the detrimental effects of erratic driving behaviors. The formulated equation describing CO emissions is expressed as (**Eq. 10**):

y (CO/km) = 0,512 – 0,219×(Eco) – 0,064×(Environment) - 0,031×(MoneyPerMonth) + 0,00005×(AvgTTL) – 0,012×(StdBrk), **(10)**

Where:

- ***CO/km***: *CO emissions per kilometer driven (g/km).*
- ***Eco****: Eco-driving scenario (e.g., 0 = Non-eco driving behavior and 1 = Eco-driving behavior)*
- ***Environment****: Driving environment (e.g., 0 = Mountainous rural network, 1 = Rural network).*
- ***MoneyPerMonth:*** *Amount spent monthly by the participant on vehicle fuel (e.g., 1 = Less than €50, 2 = €51–100, 3 = €101–200, 4 = More than €200).*
- ***AvgTTL:*** Time required for the vehicle to cross the road boundary line (ms).
- ***StdBrk:*** *Standard deviation of brake-pedal usage during driving.*

Table 4 summarizes the regression coefficients and associated statistics for each predictor in the model evaluating carbon monoxide (CO) emissions. Similar to the results in Table 3, all t-test values exceed 1.7 and all p-values remain below 0.05, indicating that each variable's effect is statistically significant at the 95% confidence level. In addition, to assess each variable's contribution to CO emissions, elasticity (e) and relative elasticity (e*) are estimated. From Table 4, Eco has the most substantial effect, 7 times the smallest (i.e., MoneyPerMonth). Likewise, Environment is twice as influential as the smallest. Among the continuous variables, StdBrk emerges as the dominant predictor, exerting an impact 25.5 times greater than that of AvgTTL.

Table 4: Model of CO/km Prediction

Independent Variables	βi	Std. Error	t Value	p-Value	e	e*
(Constant)	0.512	0.0615	8.331	0.000 ***		
Discrete variables						
Eco	-0.219	0.0225	-9.751	0.000 ***	-0.293	7.06
Environment	-0.064	0.023	-2.770	0.006 **	-0.086	2.06
MoneyPerMonth	-0.031	0.013	-2.309	0.023 *	-0.041	1.00
Continuous variables						
AvgTTL	0.00005	0.00002	2.689	0.008 **	0.00001	1.00
StdBrk	0.012	0.003	4.284	0.000 ***	0.0002	25.5
R^2 = 0.625						
Adjusted R^2 = 0.613						

* Significance at the 90% confidence level/**95%/*** 99.9%.

The regression analysis of CO emissions per kilometer validates the effectiveness of eco-driving practices, indicating a significant 29.3% reduction in emissions when transitioning from non-eco to eco-driving behavior. This reduction reflects the benefits of maintaining lower speeds, avoiding abrupt accelerations and decelerations, and reducing engine revolutions (RPM). The driving environment (Environment) also plays a crucial role, with emissions decreasing by 8.6% when driving in rural networks compared to mountainous ones. Rural terrains, characterized by fewer abrupt inclines and smoother roads, demand less frequent braking and acceleration, contributing to lower emissions. The monthly amount spent on vehicle fuel (MoneyPerMonth), with an elasticity of $e=-0.041$, suggests that drivers covering more kilometers and potentially gaining more driving experience tend to emit less CO per kilometer. Among the continuous variables, the average time required to cross the road boundary line (AvgTTL) exhibits a small positive elasticity ($e=0.00001$). Drivers who tend to stay closer to the right side of the road likely exhibit a more cautious driving profile, compared to those driving near the left lane, which may indicate an aggressive profile and a tendency for overtaking. Lastly, the standard deviation of brake usage (StdBrk) emerges as a dominant predictor with an elasticity of $e=0.0002$, showing that erratic braking behaviors and higher variability in braking intensity significantly increase CO emissions. With an R^2 value of 0.625, the model explains 62.5% of the variance in CO emissions, reinforcing the importance of eco-driving practices, stable environments, and smoother driving behaviors in reducing environmental impact.

3.3 NOx Emissions

The emission model for nitrogen oxides (NOx) identified a 34.7% or 0.02 g/km reduction attributable to eco-driving. Similarly to previous pollutant emissions, the analysis underscores that smoother and more controlled vehicular maneuvers play a pivotal role in mitigating NOx emissions. The regression model for NOx emissions is specified as (**Eq. 11**):

$$y\ (NOx/km) = 0.062 - 0.020\times(Eco) - 0.004\times(Environment) - 0.001\times(RoutesPerDay) + 0.002\times(AvgBrk) - 0.009\times(Avgrspur), \quad \textbf{(11)}$$

Where:

- ***NOx/km****: NOx emissions per kilometer driven (g/km).*
- ***Eco****: Eco-driving scenario (e.g., 0 = Non-eco driving behavior and 1 = Eco-driving behavior)*
- ***Environment****: Driving environment (e.g., 0 = Mountainous rural network, 1 = Rural network).*
- ***RoutesPerDay****: Average number of trips per day (e.g., 0 = 0 trips, 1 = 1 trip, ..., 6 = more than 5 trips).*
- ***AvgBrk****: Average brake-pedal usage (%) during driving.*

- ***Avgrspur:*** *Lateral offset of the vehicle from the center of the road (m).*

In **Table 5**, the regression coefficients and relevant statistical measures for each predictor in the nitrogen oxides (NOx) model are presented. As shown in Table 5, Eco driving compared to non-eco-driving exerts the most substantial effect 20 times greater than RoutesPerDay, which has the smallest impact. Meanwhile, Environment is 4 times as influential as the smallest. Among the continuous variables, Avgrspur affects NOx emissions 4.5 times more than AvgBrk.

Table 5: Model of NOx/km Prediction

Independent Variables	**βi**	**Std. Error**	**t Value**	**p-Value**	**e**	**e***
(Constant)	0.062	0.007	9.033	0.000 ***		
			Discrete variables			
Eco	-0.020	0.002	-11.534	0.000 ***	-0.347	20.00
Environment	-0.004	0.002	-2.168	0.032 *	-0.069	4.00
RoutesPerDay	-0.001	0.001	-2.220	0.028 *	-0.017	1.00
			Continuous variables			
AvgBrk	0.002	0.0003	6.002	0.000 ***	0.0003	1.00
Avgrspur	-0.009	0.004	-2.120	0.036 *	-0.002	-4.50
R^2 = 0.638						
Adjusted R^2 = 0.626						

* Significance at the 90% confidence level/**95%/*** 99.9%.

Based on Table 5, Eco-driving practices are shown to have a significant impact on reducing nitrogen oxides (NOx) emissions, with a 34.7% decrease in emissions when transitioning from non-eco to eco-driving. This reduction highlights the benefits of smoother driving patterns, lower speeds, and reduced engine revolutions (RPM). Driving in rural environments leads to a further 6.9% reduction in NOx emissions compared to mountainous terrains, where the frequent use of brakes and accelerators increases emissions. The average number of trips per day (RoutesPerDay) contributes a modest reduction (e=−0.017) in emissions per additional trip, likely reflecting improved driving efficiency or accumulated experience. Increased brake usage (AvgBrk) is associated with higher emissions (e=0.0003), as energy lost through braking demands greater engine power and fuel consumption. Conversely, a greater lateral offset from the center of the road (Avgrspur) reduces emissions (e=−0.002), suggesting that more conservative driving behavior, such as staying closer to the right side of the lane, is linked to lower NOx emissions. With an R^2 of 0.638, the model explains 63.8% of the variance in NOx emissions, reinforcing the importance of controlled driving habits and environmental conditions in reducing emissions.

3.4 Fuel Consumption Model

Fuel consumption exhibited comparable patterns to emissions, reflecting improvements under eco-driving scenarios. The results showed a reduction in fuel consumption of 1.050 l/100km or 7%. The statistical analysis indicates that rural driving environments and smoother driving styles significantly enhanced fuel efficiency. Gender-based differences were detected, with female drivers displaying slightly higher fuel consumption, potentially stemming from variations in braking frequency and acceleration patterns. The mathematical model governing fuel consumption is presented as (**Eq. 12**):

$$y\ (FC) = 22.125 - 1.050\times(Eco) - 1.87\times(Environment) - 0.646\times(Gender) - 0.874\times(Avgrspur) - 0.095\times(AvgClutch), \quad \textbf{(12)}$$

Where:

- ***FC:*** Fuel consumption per 100 kilometers (l/100km).
- ***Eco****: Eco-driving scenario (e.g., 0 = Non-eco driving behavior and 1 = Eco-driving behavior)*
- ***Environment****: Driving environment (e.g., 0 = Mountainous rural network, 1 = Rural network).*
- ***Gender****: Driver's gender (e.g., 1 = Male, 2 = Female).*
- ***Avgrspur:*** *Lateral offset of the vehicle from the center of the road (m).*
- ***AvgClutch:*** *Average clutch-pedal usage (percentage) during driving.*

Table 6 presents the regression coefficients and corresponding statistics for each predictor in the fuel consumption model. Moreover, the elasticity (e) and relative elasticity (e*) reveal that Environment exerts the strongest impact - roughly three times greater than the least influential factor, Gender. Similarly, Eco is 1.6 times more influential on fuel consumption than the smallest effect, while AvgClutch outweighs Avgrspur by a factor of 9.20.

Table 6: Model of Fuel Consumption Prediction

Independent Variables	βi	Std. Error	t Value	p-Value	e	e*
(Constant)	22.125	0.836	26.458	0.000 ***		
Discrete variables						
Eco	-1.050	0.155	-6.791	0.000 ***	-0.07	1.63
Environment	-1.870	0.160	-11.678	0.000 ***	-0.13	2.89
Gender	-0.646	0.152	4.262	0.000 ***	-0.04	1.00
Continuous variables						
Avgrspur	-0.874	0.368	-2.374	0.019 *	-0.0006	1.00
AvgClutch	-0.095	0.009	-10.987	0.000 ***	-0.00006	9.20
R^2 = 0.784						
Adjusted R^2 = 0.777						

* Significance at the 90% confidence level/*** 99.9%.

Fuel consumption significantly decreases under eco-driving scenarios, with an elasticity of e=−0.07, indicating a 7% improvement in efficiency when drivers adopt smoother accelerations, reduced speeds, and lower engine revolutions (RPM). Similarly, rural environments (Environment) result in a 13% reduction in fuel consumption compared to mountainous terrains, where frequent braking and acceleration are required due to steep slopes. Female drivers (Gender) consume 4% more fuel than their male counterparts, likely due to different driving patterns, such as increased braking frequency. Regarding continuous variables, the lateral offset from the center of the road (Avgrspur) demonstrates a minor effect (e=−0.0006), suggesting that drivers who maintain a more consistent position closer to the right side of the lane exhibit more fuel-efficient behavior. Finally, the average clutch usage (AvgClutch) has the most substantial impact among continuous variables (e=−0.00006), highlighting that proper clutch management improves engine performance by reducing energy losses and optimizing gear choices. With an R^2 of 0.784, the model effectively captures the factors influencing fuel consumption, reinforcing the importance of eco-driving techniques, environmental conditions, and driving behaviors for improving fuel efficiency.

3.5 Crash Probability Model

The probability model for crash risk provided further support for the hypothesis that eco-driving promotes road safety. Results demonstrated significant reductions in crash probabilities among eco-driving, particularly those adhering to stricter speed limits and possessing greater driving experience. Specifically, eco-driving was found to reduce crash probability by 66.2%, underscoring its critical role in enhancing road safety. A binary logistic model was derived for the probability of a crash based on the following relationships (**Eq. 15 & Eq. 16**):

Crash Probability = $\frac{e^{NumOfCrashesAverage}}{e^{NumOfCrashesAverage}+1}$, **(15)**

NumOfCrashesAverage = 9.248 - 2.516×(Eco) + 0.689×(Environment) - 0.233×(Age) - 1.22×(FuelMoney) - 0.41×(SpeedLimits), **(16)**

Where:

- ***NumOfCrashesAverage:*** *Indicator of crash occurrence (e.g., 0 = No and 1 = Yes).*
- ***Eco****: Eco-driving scenario (e.g., 0 = Non-eco driving behavior and 1 = Eco-driving behavior)*
- ***Environment****: Driving environment (e.g., 0 = Mountainous rural network, 1 = Rural network).*
- ***Age:*** *Driver's age (18–30 years).*
- ***FuelMoney:*** *Monthly amount spent on fuel (e.g., 1 = €0–100, 2 = More than €101).*

- ***SpeedLimits:*** *Level of agreement with reducing speed limits (e.g., 1 = Not at all, 2 = Slightly, 3 = Somewhat, 4 = Very, 5 = Extremely).*

Table 7 presents the binary logistic regression coefficients and associated statistics for each variable in the crash probability model. With the exception of Environment, whose p-value corresponds to 90% confidence, the remaining variables attain a 95% confidence level (i.e., $p < 0.05$). According to Table 7, Environment exhibits the greatest impact, approximately 39.5 times larger than FuelMoney, which shows the smallest effect on crash probability. Eco driving is 1.8 times more influential than the smallest effect, and SpeedLimits has an 8.07 stronger impact on crash probability than Age.

Table 7: Model of Crash Probability

Independent Variables	βi	Std. Error	z Value	p-Value	e	e*
(Constant)	9.248	2.613	3.540	0.000 ***		
Discrete variables						
Eco	-2.516	0.421	-5.977	0.000 ***	-0.662	1.82
Environment	0.689	0.398	1.731	0.083 *	14.365	-39.54
FuelMoney	-1.220	0.513	-2.378	0.017 **	-0.363	1.00
SpeedLimits	-0.410	0.184	-2.224	0.026 **	2.932	-8.07
Continuous variables						
Age	-0.233	0.094	-2.479	0.013 **	-0.072	-
Accuracy = 77.6%						

* Significance at the 90% confidence level/*** 99.9%.

Eco-driving practices significantly lower the probability of crash involvement, with an elasticity of e=−0.662, demonstrating that drivers adhering to smoother accelerations, reduced engine revolutions (RPM), and consistent speeds experience a substantial reduction in crash risk. Rural environments (Environment) show the strongest effect, increasing crash probability (e=14.365). This is likely due to mountainous terrain, which often features abrupt inclines and sharp curves, limiting visibility and increasing the likelihood of crashes. The amount spent monthly on fuel (FuelMoney) shows the smallest impact (e=−0.363), with higher expenditures likely reflecting greater driving experience and vehicle familiarity, contributing to safer driving. Compliant drivers with reduced speed limits (SpeedLimits) significantly lowers crash probability (e=2.932), suggesting that drivers with higher compliance levels exhibit safer driving behaviors by maintaining lower speeds. Lastly, the driver's age (Age) has a moderate negative elasticity (e=−0.072), indicating that older drivers, possibly due to their experience and caution, have a lower crash risk. The binary logistic model achieves an accuracy of 77.6%, indicating its overall effectiveness in predicting crash probabilities. Moreover, the statistically significant predictors, including eco-driving behaviors, environmental conditions, and driver characteristics, provide meaningful insights into the factors influencing crash likelihoods.

4. *Discussion*

The findings of this study underscore the diverse benefits of eco-driving, demonstrating its effectiveness in reducing environmental pollutants, optimizing fuel use, and reducing crash probabilities in rural and mountainous road environments. This discussion contextualizes these outcomes within a broader context of suitability, critically evaluating limitations while outlining theoretical and practical implications. Eco-driving emerges as a transformative paradigm in sustainable transportation and traffic safety, warranting continued scholarly and practical attention.

Empirical evidence verifies prior research confirming the effectiveness of eco-driving in curbing CO_2 emissions and fuel consumption (Coloma et al., 2020). The current study substantiates these findings by documenting a quantifiable and significant reduction of 5.9% or 19.45 g/km in CO_2 emissions within eco-driving scenarios. Coloma et al. (2020) further reported reductions in fuel consumption and CO_2 emissions ranging from 5% to 12%, contingent on driving environments, emphasizing the influence of terrain and congestion patterns. These findings highlight the value of structured driver training programs and adaptive vehicular technologies as mechanisms for embedding eco-driving methodologies into everyday practice. In modeling CO emissions, the predictive framework indicated a 29.3% or 0.219 g/km reduction associated with eco-driving. Heightened braking variability emerged as a key driver of increased emissions, underscoring how erratic driving behaviors can worsen pollutant output.

Parallel findings by Lois et al. (2019) verify the relationship between driving dynamics and overall emissions. Regarding NOx emissions, the analysis revealed a 34.7% or 0.02 g/km decline attributable to eco-driving practices. The data emphasize that maintaining steady speeds and minimizing abrupt braking significantly mitigate NOx emissions, aligning with earlier evidence. Fuel consumption exhibited similar improvements under eco-driving scenarios (i.e., reduction in fuel consumption of 1.050 l/100km or 7%), particularly in rural terrains with fewer elevation shifts. These results suggest that eco-driving not only promotes environmental sustainability but also confers economic advantages, thereby offering dual benefits for stakeholders. Similarly, Jin et al. (2015) demonstrated that eco-driving strategies optimized for intersections not only reduced CO emissions but also achieved reductions in NOx emissions (e.g., 0.11% and 17.03%, respectively), underscoring the adaptability of eco-driving techniques to various traffic scenarios (Jin et al., 2015). These results affirm eco-driving dual ecological and economic benefits, presenting compelling incentives for widespread promotion and adoption.

The current study further demonstrated a decrease in crash probabilities by 66.2% among eco-driving. Compliance with speed limits and smoother driving techniques collectively bolstered safety metrics. In a related vein, D. Robertson et al. (2024) further confirm that eco-driving reduces the risk of collisions in commercial motor vehicles by enforcing consistent speed patterns and minimizing abrupt maneuvers, contributing to improved safety metrics. Moreover, Nævestad (2022) supports this finding, indicating that eco-driving practices improve road safety by reducing accident risk through smoother driving behaviors and higher compliance with speed regulations. These insights advocate for the systematic incorporation of eco-driving principles into traffic management systems, potentially augmented by vehicle telematics and targeted infrastructure adaptations. Yang et al. (2021) reinforce this perspective, demonstrating that integrating eco-driving with intelligent traffic management and vehicle-to-infrastructure technologies can further reduce collisions and enhance operational efficiency.

The policy and practical implications of these findings are significant, spanning driver education, training, and technological innovation. Integrating eco-driving modules into driver education and licensing can normalize sustainable driving behaviors from the outset, fostering environmental responsibility among both novice and experienced drivers. For drivers, particularly those operating in challenging terrains, targeted interventions focusing on adaptive techniques for varying gradients and conditions may yield considerable emissions reductions and improved safety outcomes. The incorporation of real-time in-vehicle feedback systems, as demonstrated by Ng et al. (2021), has also been shown to enhance fuel efficiency and reduce emissions, providing immediate behavioral cues to drivers. Equally important, Adamczak et al. (2020) underscore the role of structured incentives, such as financial rewards and discounts, in cultivating sustained compliance with eco-driving practices, resulting in measurable improvements in emission profiles. Finally, policymakers could amplify these effects by employing economic instruments, such as tax incentives or insurance premium reductions, to accelerate the adoption of eco-driving technologies and training programs.

Aside from the study contributions, this research acknowledges certain limitations. Although a driving simulator enables controlled experimentation, its ecological validity is constrained, necessitating further on-road evaluations. Additionally, the young-aged of the participants restricts somehow the generalizability of the findings, highlighting the importance of larger, more diverse participant pools in subsequent investigations. Moreover, cultural and regional gradations merit exploration to tailor eco-driving strategies effectively across various contexts.

Future research could investigate the longitudinal effects of eco-driving training, assessing behavioral retention and possible evolution over extended periods. The interface between eco-driving and emerging automotive technologies—particularly in electric and hybrid vehicles—remains a promising area of inquiry (Neumann et al., 2015). Studies examining adaptive cruise control, lane-keeping systems, and associated driver-assistance technologies may uncover synergistic effects that further enhance both environmental outcomes and road safety. Additionally, exploring how infrastructure design influences eco-driving efficacy, especially in mountainous regions, could provide actionable insights for policymakers and urban planners.

In conclusion, this work delineates the multidimensional advantages of eco-driving namely, emission reduction, improved fuel efficiency, and decreased crash risks in rural and mountainous environments. It establishes a substantive basis for extending eco-driving through policy reforms, technological developments, and infrastructural investments. While longitudinal and real-world validations remain essential, the evidence presented underscores eco-driving integral role within sustainable transportation frameworks. Moving forward, coordinated efforts among policymakers, researchers, and automotive industry stakeholders will be critical to realizing its full ecological and economic potential.

5. *Conclusions*

This investigation offers strong evidence for incorporating eco-driving strategies as a practical way to improve environmental sustainability, boost fuel efficiency, and enhance road safety. Through empirical models focused on CO_2, CO, and NOx emissions, as well as fuel consumption, the study illustrates how eco-driving can notably cut both emissions and fuel usage, leading to positive ecological and economic outcomes. The findings indicate that eco-driving not only reduces pollutants but also reduces collision risks, reinforcing the argument for its wider acceptance.

One standout aspect of this research is its integration of eco-driving principles in experimental settings to measure outcomes accurately in both rural and mountainous environments. Unlike many past studies focusing mainly on urban contexts, this work addresses eco-driving's effectiveness in more demanding terrains, bridging an important research gap. By using advanced regression analysis, the study establishes credible evidence that eco-driving cuts emissions, boosts fuel economy, and promotes safer roads.

Overall, this research identifies eco-driving as a pivotal strategy within the broader context of sustainable transport. Its diverse benefits, ranging from emission reductions and fuel savings to lower crash risks, point to a need for concerted efforts among policymakers, academia, and industry players to promote eco-driving. Future initiatives should refine training methods, explore technological advancements, and implement supportive policies to fully harness the environmental and financial rewards eco-driving can offer.

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