Interactions among Road, Vehicle and Driver Risk Factors for the Identification of Safety Tolerance Zone

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ABSTRACT

Road safety is a complex issue influenced by a wide range of factors, including driver characteristics, environmental conditions and traffic variables. The aim of this study was to identify the interactions among road environment, vehicle state and driver behavior for the identification of the Safety Tolerance Zone (STZ). More specifically, the impact of task complexity and coping capacity on crash risk was examined. Towards that end, a naturalistic driving experiment was conducted, involving 135 drivers and a large database of 31,954 trips was collected. Exploratory analyses, such as Generalized Linear Models (GLMs) were developed and the most appropriate variables associated to the latent variable task complexity and coping capacity were estimated from the various indicators. In addition, Structural Equation Models (SEMs) were used to explore how the model variables were inter-related, allowing for both direct and indirect relationships. Results showed positive correlation of task complexity and coping capacity that implies that driver's coping capacity increased as the complexity of driving task increases. It was demonstrated that task complexity was positively correlated with risk, indicating that driving during night-time or in adverse weather conditions can exacerbate the challenges posed by complex tasks, further increasing the likelihood of crashes. On the other hand, coping capacity was negatively correlated with risk, indicating that drivers with higher coping capacity are better equipped to handle challenging driving situations. The integrated treatment of task complexity, coping capacity and risk can improve behavior and safety of all travellers, through the unobtrusive and seamless monitoring of behavior.

Keywords: Road environment, Vehicle State, Driver Behavior, Safety Tolerance Zone, Generalized Linear Models, Structural Equation Models.

INTRODUCTION

Road traffic crashes result in the deaths of approximately 1.19 million people around the world each year and leave between 20 and 50 million people with non-fatal injuries *(1)*. According to World Health Organization, more than half of all road traffic deaths occur among vulnerable road users, such as pedestrians, cyclists and motorcyclists. Road traffic injuries are the leading cause of death for children and young adults aged 5-29.

Several factors have a significant impact on road safety. These factors can contribute to the occurrence of road crashes and influence the severity of injuries sustained. For instance, human behavior plays a critical role in road safety, accounting for 65-95% of road crashes *(2)*. Factors such as speeding, distracted driving, impaired driving, aggressive driving, and non-compliance with traffic regulations can increase the crash risk *(3)*. In addition, the condition and safety features of vehicles also play a critical role in averting crashes and reducing the likelihood of serious. Indicators such as vehicle maintenance, tire condition, brake functionality, and the presence of safety technologies can significantly affect crash outcomes *(4)*. Similarly, environmental conditions can affect road safety. Factors such as adverse weather conditions, poor visibility, and uneven road surfaces can increase the likelihood of crashes *(5)*. Moreover, the design, condition, and maintenance of roads and infrastructure can impact road safety *(6)*.

Considering all the aforementioned arguments, road safety is a complex issue influenced by a wide range of factors, including driver characteristics, environmental conditions and traffic variables. This forms the motivation of this study, aiming to investigate the interactions among road environment, vehicle state and driver behavior, and their impact on crash risk.

The ultimate goal of this paper is to develop a context-aware 'Safety Tolerance Zone'. This Safety Tolerance Zone (STZ) refers to a context-sensitive and dynamic zone in which the driver is within acceptable boundaries of safe operation, and thus not in immediate risk of a crash. Based on the integration of emerging technologies in the European Union's commitment to improve road safety and minimize road fatalities, the European H2020 project i-DREAMS aims to define, develop, test, and validate a 'Safety Tolerance Zone' (STZ). Through a smart system, i-DREAMS aims to identify the level of 'STZ', by monitoring and evaluating risk indicators related to the complexity of the driving task as well as the ability to cope with the challenges posed by it, and thus support drivers to operate within safe boundaries. The calculation of this zone happens on a continuous real-time assessment by monitoring the driver and environment, taking into account, on the one hand, driver-related background factors (e.g. gender, speeding) and real-time risk-related physiological indicators (e.g. fatigue), and on the other hand, driving task-related complexity indicators (e.g. time of day, adverse weather) and vehicle indicators (e.g. fuel type, vehicle age).

The concept of the STZ attempts to describe the point at which self-regulated control is considered safe. Simply described, it is the zone where the demands of the driving task (task complexity) are balanced with the ability of the driver to cope with them (coping capacity). The STZ comprises three phases: normal driving, danger and avoidable accident phase. The normal driving refers to the phase where conditions at that point in time suggest that a crash is unlikely to occur and therefore the crash risk is low and the operator is successfully adjusting their behavior to meet task demands. The danger phase is characterised by changes to the normal driving that suggest a cash may occur and therefore, there is an increased crash risk. At this stage a crash is not inevitable but becomes more likely. The STZ switches to the danger phase whenever instantaneous measurements detect changes that imply an increased crash risk. Lastly, the switch to avoidable accident phase occurs when a collision scenario is developing but there is still time for the operator to intervene in order to avoid the crash. In this phase, the need for action is more urgent as if there are no changes or corrections in the road or rail traffic system or an evasive manoeuvre is performed by the operator a crash is very likely to occur.

The fundamental challenge within this research is how explanatory variables (i.e. performance metrics and indicators of task complexity and coping capacity) are correlated with the dependent variable risk in order to predict STZ levels. In order to fulfill these objectives, a naturalistic driving experiment was conducted, involving a total of 135 drivers aged 20-65. Safety-oriented interventions were developed to prevent drivers from approaching the boundaries of unsafe operation and guide them back into the STZ.

The paper is structured as follows. In the beginning, the motivation and the objectives of this study, along with the concept of the STZ are described. This is followed by the description of the research methodology, encompassing the theoretical foundations of the models utilized. Then, a detailed overview of data collection is presented. Finally, the results of the analysis are presented followed by relevant discussion on key findings. Lastly, safety recommendations are also provided.

METHODOLOGY

Generalized Linear Models

To begin with, linear regression is one of the most widely studied and applied statistical and econometric techniques. First, linear regression is suitable for modeling a wide variety of relationships between variables. In addition, the assumptions of linear regression models are often suitably satisfied in many practical applications. Furthermore, regression model outputs are relatively easy to interpret and communicate to others, numerical estimation of regression models is relatively easy, and software for estimating models is readily available in numerous “non-specialty” software packages. Linear regression can also be overused or misused. In some cases, the assumptions are not strictly met, and suitable alternatives are not known, understood, or applied *(7)*.

In statistics, the Generalized Linear Model (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value *(8)*.

The application of GLMs stands as a pivotal asset in comprehending the intricate interplay between task complexity, coping capacity, and driving risk *(9)*. In general, a GLM-based approach utilizes a linear regression to aggregate a series of independent variables, such as roadway curvature, shoulder width, traffic speed limit, etc. and establish a mapping relationship between independent variables and dependent variable (which is typically the expected value of crash rates) through a specific link function. In a GLM, each outcome Y of the dependent variables is assumed to be generated from a particular distribution in an exponential family, a large class of probability distributions that includes the normal, binomial, Poisson and gamma distributions, among others. The mean, μ, of the distribution depends on the independent variables, X, through:

$$E(Y|\mathrm{X}) = \mu = g^{-1}(X\beta) \tag{1}$$

where: E(Y|X) is the expected value of Y conditional on X; Xβ is the linear predictor, a linear combination of unknown parameters β; g is the link function.

In this framework, the variance is typically a function, V, of the mean:

$$Var(Y|\mathrm{X}) = V(g^{-1}(X\beta)) \tag{2}$$

It is convenient if V follows from an exponential family of distributions, but it may simply be that the variance is a function of the predicted value. The unknown parameters, β, are typically estimated with maximum likelihood, maximum quasi-likelihood, or Bayesian techniques.

GLMs were formulated as a way of unifying various other statistical models, including linear regression, logistic regression and Poisson regression. In particular, Hastie & Tibshirani *(8)* proposed an iteratively reweighted least squares method for maximum likelihood estimation of the model parameters. Maximum-likelihood estimation remains popular and is the default method on many statistical computing packages. A key point in the development of GLM was the generalization of the normal distribution (on which the linear regression model relies) to the exponential family of distributions. This idea was developed by Collins et al. *(10)*. Consider a single random variable y whose probability (mass) function (if it is discrete) or probability density function (if it is continuous) depends on a single parameter θ. The distribution belongs to the exponential family if it can be written as follows:

$$f(y;\theta) = s(y)t(\theta)e^{a(y)b(\theta)} \quad (3)$$

where: a, b, s, and t are known functions. The symmetry between y and θ becomes more evident if the equation above is rewritten as follows:

$$f(y;\theta) = \exp\,[\alpha(y)b(\theta) + c(\theta) + \; d(y)] \quad (4)$$

where: s(y)=exp[d(y)] and t(θ)=exp[c(θ)]

If a(y) =y then the distribution is said to be in the canonical form. Furthermore, any additional parameters (besides the parameter of interest θ) are regarded as nuisance parameters forming parts of the functions a, b, c, and d, and they are treated as though they were known. Many well-known distributions belong to the exponential family, including Poisson, normal or binomial distributions. On the other hand, examples of well-known and widely used distributions that cannot be expressed in this form are the student's t-distribution and the uniform distribution.

It should be mentioned that the Variance Inflation Factor (VIF) is a measure of the amount of multicollinearity in regression analysis. Multicollinearity exists when there is a correlation between multiple independent variables in a multiple regression model. The default VIF cut-off value is 5; only variables with a VIF less than 5 will be included in the model (VIF<5). However, in certain cases, even if VIF is less than 10, then it can be accepted.

Structural Equation Models

Structural Equation Model (SEM) represent a natural extension of a measurement model, and a mature statistical modeling framework. SEM is widely used for modeling complex and multi-layered relationships between observed and unobserved variables, such as task complexity or coping capacity. Observed variables are measurable, whereas unobserved variables are latent constructs – analogous to factors/components in a factor/principal component analysis.

It should be noted that SEMs has been widely used for modeling road user behavior and safety. First of all, SEMs have emerged as a powerful tool for analysing the intricate interplay between observed variables and latent constructs in road safety research. They allow researchers to explore the direct and indirect effects of multiple factors on road safety while providing a methodology for direct modeling of latent variable, separating measurement errors from true scores of attributes *(11)*. This makes SEMs particularly suitable for studying the multifaceted nature of road safety, where numerous factors interact to influence the occurrence and severity of crashes. One area where SEMs have been applied in road safety is the modeling of driver behavior and its impact on crash occurrence. By incorporating multiple variables, such as driver characteristics, environmental factors, and vehicle conditions, SEMs provide insights into their combined influence on driving behavior and crash severity *(12)*.

SEMs have two components: a measurement model and a structural model. The measurement model is used to determine how well various observable exogenous variables can measure the latent variables, as well as the related measurement errors. The structural model is used to explore how the model variables are inter-related, allowing for both direct and indirect relationships to be modeled. In this sense, SEMs differ from ordinary regression techniques in which relationships between variables are direct.

The general formulation of SEM is as follows *(7)*:

$$\eta = \beta\eta + \gamma\xi + \varepsilon \tag{5}$$

where: η is a vector of endogenous variables, ξ is a vector of exogenous variables, β and γ are vectors of coefficients to be estimated, and ε is a vector of regression errors.

The measurement models are then as follows *(13)*:

$$x = \Lambda_x\xi + \delta, \text{ for the exogenous variables} \tag{6}$$

$$y = \Lambda_y\eta + \zeta, \text{ for the endogenous variables} \tag{7}$$

where: x and δ are vectors related to the observed exogenous variables and their errors, y and ζ are vectors related to the observed endogenous variables and their errors, and Λ_x, Λ_y are structural coefficient matrices for the effects of the latent exogenous and endogenous variables on the observed variables.

The structural model is often represented by a path analysis, showing how a set of 'explanatory' variables can influence a 'dependent' variable. The paths can be drawn so as to reflect whether the explanatory variables are correlated causes, mediated causes, or independent causes to the dependent variable.

Figure 1 shows a graphical representation of two different linear regression models with two independent variables, as is often depicted in the SEM nomenclature. The independent variables X1 and X2, shown in rectangles, are measured exogenous variables, with direct effects on variable Y1, are correlated with each other. The model depicted in the bottom of the Figure reflects a fundamentally different relationship among variables. Variables X3 and X4 directly influence Y2, but variable X4 is also directly influenced by variable X3. The two models imply different var-cov matrices. Both models also reveal that although the independent variables have direct effects on the dependent variable, they do not fully explain the variability in Y, as reflected by the error terms, depicted as ellipses in the **Figure 1**. The additional error term, e3, describes and comprises the portion of variable X4, which cannot by fully explained by the effect of variable X3. Latent variables, if added to these models, would also be depicted as ellipses in the graphical representation of the SEM.

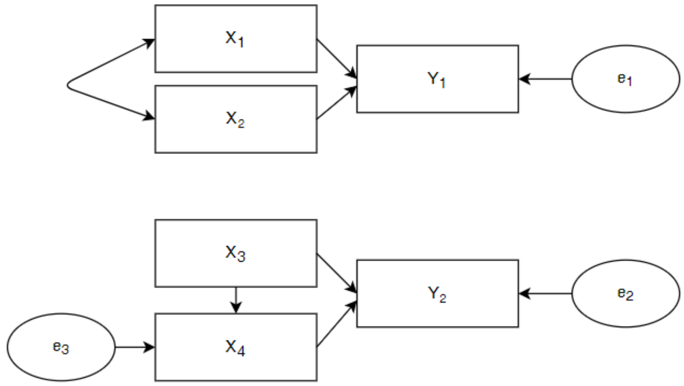

Figure 1 SEMs depicting standard linear regression model with two variables

Evaluation metrics

In the context of model selection, model Goodness-of-Fit measures consist an important part of any statistical model assessment. A detailed description of the aforementioned metrics is presented below:

The Akaike Information Criterion (AIC), which accounts for the number of included independent variables, is used for the process of model selection between models with different combination of explanatory variables.

$$AIC = -2L(\theta) + q \tag{8}$$

where: q is the number of parameters and L(θ) is the log-likelihood at convergence. Lower values of AIC are preferred to higher values because higher values of -2L(θ) correspond to greater lack of fit.

The Bayesian Information Criterion (BIC) is used for model selection among a finite set of models; models with lower BIC are generally preferred.

$$BIC = -2L(\theta) + q \ln(N) \tag{9}$$

The Comparative Fit Index (CFI) is based on a noncentral x^2 distribution. It evaluates the model fit by comparing the fit of a hypothesized model with that of an independence model. In general, values more than 0.90 for CFI are generally accepted as indications of very good overall model fit (CFI>0.90). The formula is represented as follows:

$$CFI = 1 - \frac{\max({x_H}^2 - df_H, 0)}{\max({x_H}^2 - df_H, {x_I}^2 - df_I)} \tag{10}$$

where: x^2_H is the value of x^2 and df_H is degrees of freedom in the hypothesized model, and x^2_I is the value of x^2 and df_I is the degrees of freedom in the independence model.

The Tucker Lewis Index (TLI) considers the parsimony of the model. Values more than 0.90 for TLI are generally accepted as indications of very good overall model fit (TLI>0.90). The formula is represented as follows:

$$TLI = \frac{\frac{x_I{}^2}{df_I} - \frac{x_H{}^2}{df_H}}{\frac{x_I{}^2}{df_I} - 1} \quad (11)$$

where: x^2_H is the value of x^2 and df_H is the degrees of freedom in the hypothesized model, and x^2_I is the value of x^2 and df_I is the degrees of freedom in the independence model.

Currently, one of the most widely used goodness-of-fit indices is the Root Mean Square Error Approximation (RMSEA) which measures the unstandardized discrepancy between the population and the fitted model, adjusted by its degrees of freedom (df). The formula is represented as follows:

$$RMSEA = \sqrt{\frac{x_H{}^2 - df_H}{df_H(n-1)}} \quad (12)$$

where: x^2_H is the value of x^2 and df_H is the degrees of freedom in the hypothesized model; n is the sample size.

The Goodness of Fit Index (GFI) is a measure of fit between the hypothesized model and the observed covariance matrix *(14)*. Values more than 0.90 for GFI are generally accepted as indications of very good overall model fit (GFI>0.90).

DATA DESCRIPTION

A naturalistic driving experiment was carried out involving 135 drivers and a large database of 31,954 trips was collected and analysed in order to investigate the most prominent driving behavior indicators, including speeding, headway, duration, distance and harsh events. The naturalistic driving experiment focused on monitoring driving behavior and the impact of real-time interventions (i.e. in-vehicle warnings) and post-trip interventions (i.e. post-trip-feedback & gamification) on driving behavior. The experimental design was divided into four consecutive phases:

- Phase 1: monitoring (baseline measurement)
- Phase 2: real-time intervention
- Phase 3: real-time intervention and post-trip feedback
- Phase 4: real-time intervention and post-trip feedback and gamification

Firstly, phase 1 of the field trials refers to a reference period after the installation of the system inside the vehicle in order to monitor driving behavior without interventions. Secondly, phase 2 of the field trials refers to a monitoring period during which only in-vehicle real-time warnings were provided using Advanced Driver Assistance Systems (ADAS). Thirdly, in phase 3 of the field trials, feedback via the smartphone app is combined with in-vehicle warnings. Lastly, in phase 4 of the field trials, gamification features are added to the app, with additional support of a web-dashboard.

An integrated set of monitoring and communication tools for intervention and support, state-of-the-art technologies and systems were utilized to monitor driving performance indicators. Vehicles were equipped with Mobileye and CardioDashcam which monitor the road and the driving process and record events for post-trip analysis. Additionally, PulseOn wearable was used for drowsiness/sleepiness detection. In the intervention perspective, the intervention device was installed and communicated with CardioGateway to receive the status of the STZ and provide visual and sound alerts in real-time, allowing as well the identification of the driver, in a scenario of multiple drivers per vehicle. Finally, a smartphone application was also available not only to monitor the mobile phone use while driving, as an indicator of distraction, but also for post-trip feedback, to engage drivers on their performance improvement, through a gamification strategy, that includes but is not limited to rating and scores. The technology described in **Figure 2** measures the environment, vehicle and driver indicators used to define task complexity and coping capacity in order to calculate which phase of the STZ the driver is operating within.

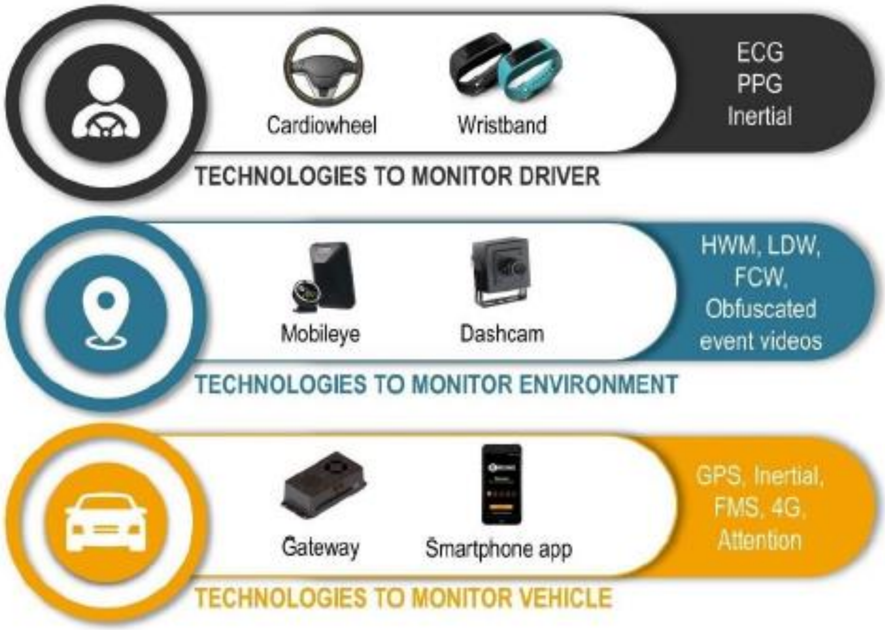

Figure 2 Technologies to monitor driver, environment and vehicle state

Figure 3 demonstrates the most relevant variables utilized to define task complexity and coping capacity, from both vehicle and operator state. These variables are instrumental to this study, essential for capturing the complex dynamics of the interrelationship among task complexity, coping capacity and risk.

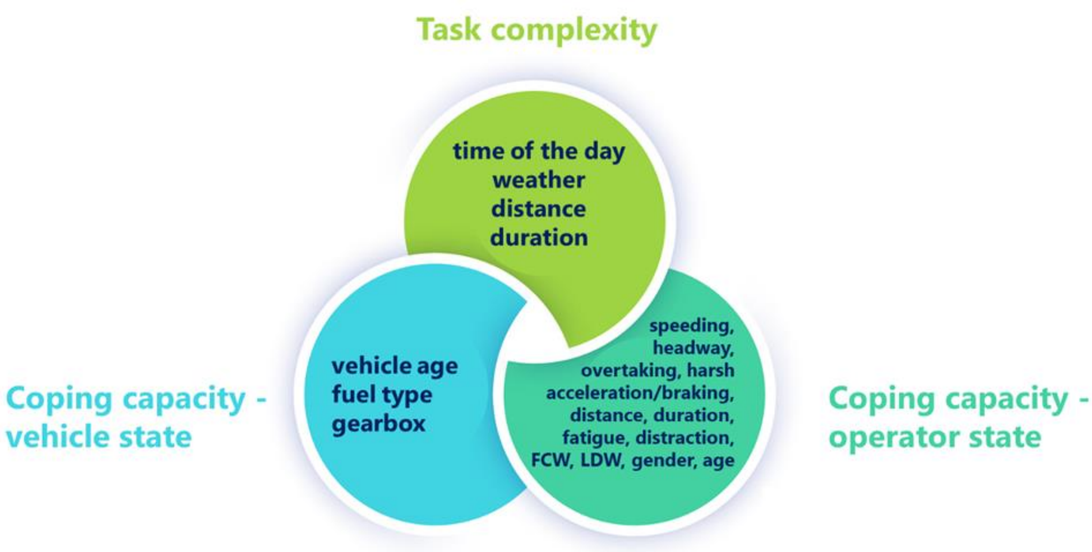

Figure 3 Variables of task complexity and coping capacity

RESULTS

Regression analyses (GLM)

A high number of regression model tests were conducted for different combinations of variables. An attempt was made to use the same independent variables in the model applied. For each configuration, various alternatives were tested through the respective log-likelihood test comparisons.

The relationship between speeding and risk is widely recognized in the road safety community and as such, speeding is a commonly used dependent variable in transportation human factors research. The GLM applied investigated the relationship between speeding and several explanatory variables of task complexity and coping capacity (both vehicle and operator state). In particular, the dependent variable of the developed model is the dummy variable "speeding", which is coded with 1 if there is a speeding event and with 0 if not. For task complexity, the variables used are time indicator and wipers. It should be noted that the wipers variable indicates the state of the windshield wipers, which can be used to infer weather conditions. With regards to coping capacity - vehicle state, the variables used are fuel type, vehicle age and gearbox, while for coping capacity - operator state, the variables used are duration, distance travelled, harsh acceleration, harsh braking, gender and age. The model parameter estimates are summarized in **Table 1**.

It can be observed that all explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity as the VIF values are much lower than 5. With regard to the coefficients, it was revealed that the indicators of task complexity, such as time indicator and wipers were positively correlated with speeding. The former refers to the time of the day (day coded as 1, dusk coded as 2, night coded as 3) which means that higher speeding events occur at night compared to during the day. This may be due to fewer cars on the road, lower visibility, and a false sense of security that comes with driving in the dark. Interestingly, wipers (wipers off coded as 1, wipers on coded as 2) were also found to have a positive correlation with speeding which means that there are more speeding events during adverse (e.g. rainy) weather conditions. This may be due to the fact that wet and slippery roads can make it more difficult to maintain control of the vehicle. Additionally, rain can reduce visibility and make it harder to see other cars or obstacles on the road.

TABLE 1 Parameter estimates and multicollinearity diagnostics of the GLM for speeding

Variables	**Estimate**	**Std. Error**	**z-value**	**Pr(|z|)**	**VIF**
(Intercept)	-0.618	0.004	-162.415	< .001	-
Time indicator	0.033	0.002	15.172	< .001	1.154
Weather	0.058	0.008	7.609	< .001	1.007
Fuel type - Diesel	-5.904×10^{-6}	1.863×10^{-6}	-3.169	0.002	4.548
Vehicle age	1.212×10^{-4}	2.009×10^{-6}	60.317	< .001	3.482
Gearbox - Automatic	-1.231×10^{-5}	2.321×10^{-6}	-5.302	< .001	2.175
Duration	5.123×10^{-6}	2.900×10^{-7}	17.664	< .001	1.111
Distance	1.820×10^{-5}	8.235×10^{-7}	22.096	< .001	1.091
Harsh acceleration	8.358×10^{-5}	2.222×10^{-6}	37.609	< .001	2.892
Harsh braking	5.776×10^{-5}	2.055×10^{-6}	28.104	< .001	2.883
Gender - Female	-3.295×10^{-6}	1.813×10^{-6}	-1.818	0.069	1.555
Age	-1.210×10^{-4}	2.285×10^{-6}	-52.977	< .001	4.062
Summary statistics					
AIC	1.231×10+6				
BIC	1.051×10+6				
Degrees of freedom	822174				

Regarding the indicators of coping capacity – vehicle state, vehicle age was found to be positively correlated with speeding, meaning that as vehicles get older, the likelihood of speeding incidents increases. This means that the increased proportion of older vehicles increases the risk to exceed the speed limits. This was probably due to the fact that in the current years, with the permanent development and safety improvements of the automotive sector, newer vehicles are equipped with ADAS features, such as adaptive cruise control, automatic emergency braking and speed limit recognition, which actively help reduce speeding and enhance overall driving safety.

On the other hand, fuel type and gearbox were negatively correlated with speeding. More specifically, the negative value of the variable "fuel type" coefficient implied that when the fuel type was diesel (diesel coded as 1, hybrid electric coded as 2 and petrol coded as 3), the speeding percentage became lower. This indicated that vehicles with gasoline-powered engines provided higher speeding events compared to other types of vehicles, such as electric and hybrid cars. Similarly, the negative value of the variable "gearbox" coefficient demonstrated that vehicles with automatic gearbox experienced fewer speeding events compared to those with manual gearbox. This suggests that drivers of automatic vehicles are less likely to speed, potentially due to the smoother and more controlled driving experience provided by automatic transmissions.

Furthermore, it was demonstrated that indicators of coping capacity – operator state, such as duration, distance travelled, harsh acceleration and harsh braking had a positive relationship with the dependent variable (i.e. speeding), indicating that as the values of the aforementioned independent variables increase, speeding also increases. This is a noteworthy finding of the current research as it confirms that harsh driving behavior events present a statistically significant positive correlation with speeding.

Taking into consideration socio-demographic characteristics, gender and age were negatively correlated with speeding. In particular, the negative value of the "gender" coefficient implied that as the value of the variable was equal to 1 (males coded as 0, females as 1), the speeding percentage was lower. Results revealed that the vast majority of male drivers displayed less cautious behavior during their trips and exceeded more often the speed limits than female drivers. It is also remarkable that the negative value of the "age" coefficient implied that as the value of the variable increased (higher value indicates increased age and, therefore, increased years of participant's experience), the speeding percentage was lower. Young drivers appeared to have a riskier driving behavior than older drivers and were more prone to exceed the speed limits.

Latent analyses (SEM)

Following the exploratory analysis, the variables associated to the latent variable "task complexity" and "coping capacity" were estimated from the various indicators. This way, the effect of different personal factors on risk was defined and further analysed. Several SEM were applied in order to identify the effect of task complexity and coping capacity on the STZ level, controlling for the above exogenous factors. Risk is measured by means of the STZ levels for speeding (level 1 refers to 'normal driving' used as the reference case; level 2 refers to 'dangerous driving' while level 3 refers to 'avoidable accident driving'). In particular, positive correlations of risk with the STZ indicators were found.

To begin with, the latent variable of task complexity is measured by means of the environmental indicator of time of the day. It should be noted that based on the definition of task complexity, road layout, time, location and traffic volumes should be included in the analysis. However, road type (i.e. urban, rural, highway), location and traffic volumes (i.e. high, medium, low) were not available. Thus, only the time indicator and weather were able to be used in the models applied. To that aim, exposure indicators, such as trip duration and distance travelled were included in the task complexity analysis. In particular, time of the day, distance and duration found to have a positive correlation with task complexity.

Furthermore, it is shown that the latent coping capacity is measured by means of both vehicle and operator state indicators. Vehicle state includes variables such as "vehicle age" (indicating the age of the vehicle), "gearbox" (indicating the type of gearbox; automatic or manual) and "fuel type" (indicating the type of fuel; diesel, hybrid electric, petrol). At the same time, operator state indicators, such as "gender" (indicating the gender of the driver; male or female) and "headway" (indicating the time distance between the front of the driver's vehicle and the front of the vehicle ahead) are included in the SEM applied. Results indicated that vehicle age, gearbox, gender and driver's age were negatively correlated with coping capacity. This suggests that older vehicles, the type of gearbox and certain gender and age drivers' demographic characteristics are associated with a decreased ability to manage and respond to driving demands and challenges effectively.

The SEM among the latent variables shows some interesting findings: first, task complexity and coping capacity are inter-related with a positive correlation (regression coefficient=0.47). This positive correlation indicates that higher task complexity is associated with higher coping capacity implying that drivers coping capacity increases as the complexity of driving task increases. Overall, the SEM between task complexity and risk shows a positive coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=10.67). On the other hand, the structural model between coping capacity and risk shows a negative coefficient, which means that increased coping capacity relates to decreased risk according to the model (regression coefficient=-2.06). The respective path diagram of the SEM for speeding is presented in **Figure 4.**

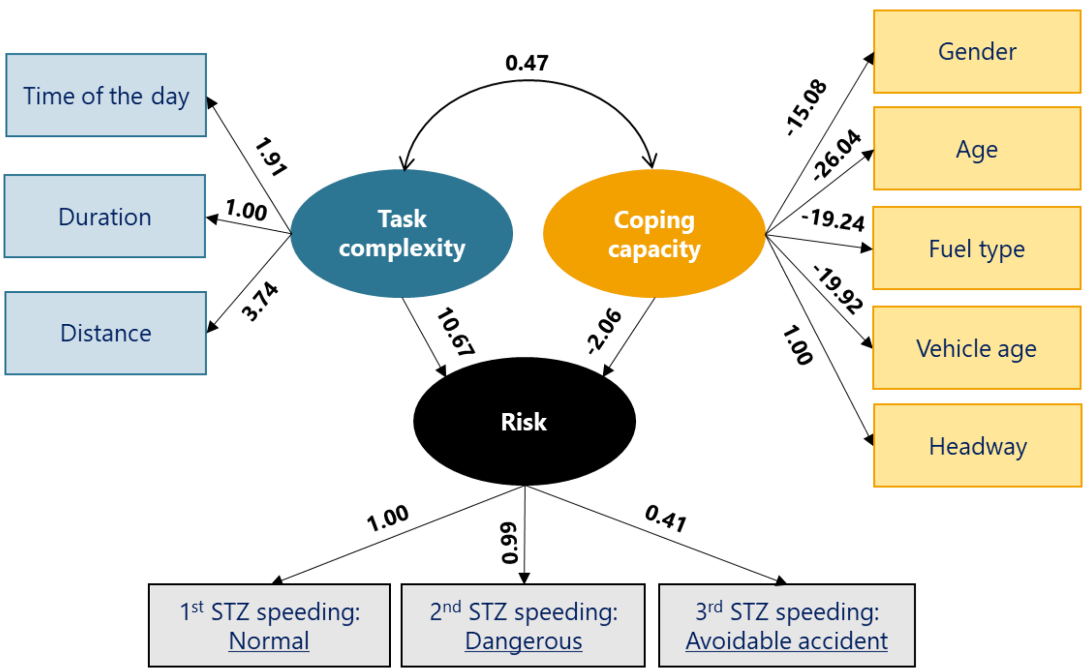

Figure 4 SEM results of task complexity and coping capacity on risk (STZ speeding)

In order to have a clear picture per each phase, four separate SEM models were estimated in order to explore the relationship between the latent variables of task complexity, coping capacity and risk (expressed as the three phases of the STZ) of speeding. Each model corresponds with one of the different experiment phases:

- Phase 1: monitoring (6,940 trips)
- Phase 2: real-time interventions (6,189 trips)
- Phase 3: real-time & post-trip interventions (6,776 trips)
- Phase 4: real-time, post-trip interventions & gamification (7,816 trips)

Figure 5 shows the graphical structure of the SEM results of the different phases of the experiment. It is observed that the measurement equations of task complexity and coping capacity are fairly consistent among the different phases. At the same time, the loadings of the observed proportions of the STZ of speeding are consistent among the different phases. The structural model between task complexity and risk are positively correlated among the four phases, while coping capacity and risk found to have a negative relationship in all phases of the experiment.

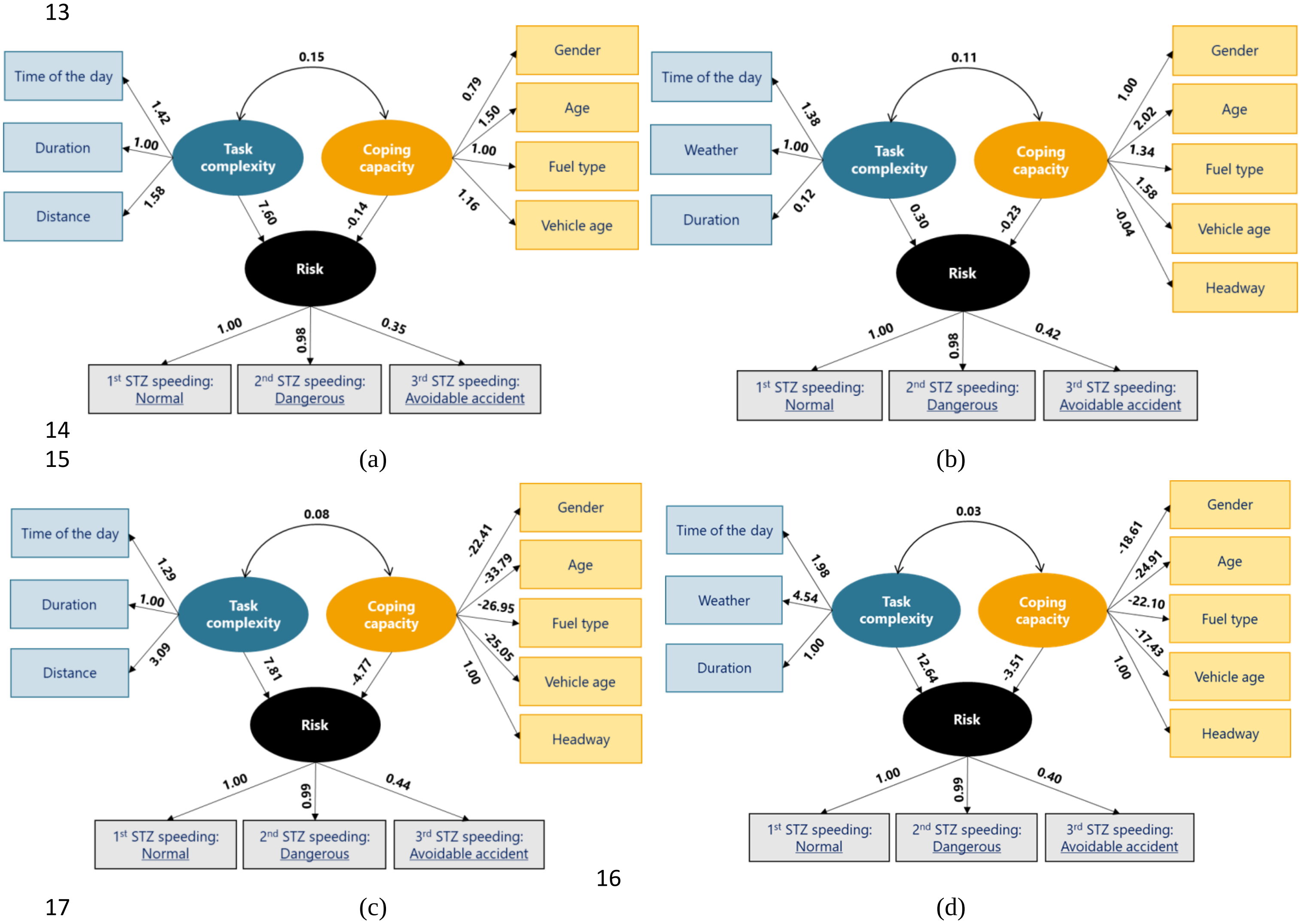

Figure 5 SEM results of task complexity and coping capacity on risk (STZ speeding) - Experiment phase 1 (a), 2 (b), 3 (c), 4 (d)

Table 2 summarizes the model fit of SEM applied for speeding for the different experiment phases. The Comparative Fit Index (CFI) of the overll model is equal 0.920; Tucker Lewis Index (TLI) is 0.893 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.095.

TABLE 2 Model Fit Summary for speeding for the different experiment phases

Model Fit measures	Phase 1	Phase 2	Phase 3	Phase 4	Total
	Value				
CFI	0.927	0.822	0.898	0.903	0.920
TLI	0.897	0.761	0.863	0.870	0.893
RMSEA	0.100	0.158	0.108	0.110	0.095
GFI	0.940	0.874	0.918	0.913	0.932
Hoelter's critical N (α = .05)	246.410	256.591	320.534	315.308	253.706
Hoelter's critical N (α = .01)	269.362	264.409	337.344	331.383	275.180
AIC	3.166×10+6	4.690×10+6	5.446×10+6	7.231×10+6	2.258×10+7
BIC	3.166×10+6	4.690×10+6	5.446×10+6	7.231×10+6	2.258×10+7

DISCUSSION

Within the framework of the regression analysis, the effect of road environment, vehicle state and driver behavior on crash risk was examined and several significant results were extracted. The research found a positive correlation between the time of day and speeding. This trend suggests that drivers tend to speed more as it gets later in the day, with the highest rates of speeding occurring at night. This could be due to reduced traffic, lower visibility and possibly a decrease in perceived risk during these times. This is in line with previous observations by the authors, who found that road lighting leads to increased speeds and reduced levels of concentration with an increase in average speed on straight and curved sections of about 5% and 1%, respectively *(15)*. Interestingly, speeding was positively correlated with adverse weather conditions (wipers on), indicating more speeding events during rain. This may be because wet and slippery roads make it harder to maintain control and reduced visibility can obscure obstacles and other vehicles.

With regards to the indicators of coping capacity – vehicle state, a positive correlation between vehicle age and speeding was identified. This finding indicates a critical road safety issue: as vehicles age, the likelihood of exceeding speed limits increases. This heightened risk is attributed to the deterioration of vehicle components and the absence of modern safety features in older vehicles. Török *(16)* reinforces this argument by suggesting that phasing out older vehicles, particularly those over 15 years old, can significantly improve road safety. This improvement is likely due to the integration of ADAS and better overall vehicle performance in newer models, which help in maintaining safe driving behaviors and reducing the propensity for speeding. On the other hand, the vehicle state indicator of fuel type was negatively correlated with speeding. This implied that vehicles with diesel fuel type experienced fewer speeding events compared to those with gasoline. This difference could be due to various factors, such as the typical use cases for diesel vehicles, which are often designed for long-distance and heavy-duty use, leading to more conservative driving behaviors.

Furthermore, it was demonstrated that the majority of the indicators of coping capacity – operator state had a positive relationship with speeding. In particular, exposure indicators, such as duration and distance travelled were positively correlated with speeding which means that the longer the duration and the greater the distance a vehicle travelled, the more likely it was to exceed the speed limits. This correlation might be due to the fact that drivers becoming more comfortable and confident over longer trips, leading to an increase in speed, or it could reflect the tendency of drivers to speed in order to cover longer distances more quickly. This finding is in line with Fildes et al. *(17)*, who claimed that drivers in rural areas who were observed travelling above the average speed were likely to be males travelling over long distances for other than domestic journeys. Regarding harsh events, harsh acceleration and harsh braking were positively correlated with speeding, indicating that aggressive driving behaviors led to higher speeds and greater distances between vehicles.

Lastly, the GLMs applied have revealed interesting findings concerning socio-demographic characteristics, particularly gender and age. It was shown that female drivers were less likely to speed and tended to maintain larger distances from the vehicle in front of them compared to their male counterparts. Additionally, it was observed that older drivers were less likely to engage in speeding, demonstrating a negative correlation between age and speeding events. Overall, young drivers exhibited riskier driving behavior, being more prone to exceed speed limits.

Through the application of SEM models, the analyses revealed that higher task complexity led to higher coping capacity by the vehicle operators. It was found that when drivers encountered complex tasks, such as driving during risky hours (22:00-05:00) or adverse weather conditions, they were compelled to engage more deeply with the driving process and tended to regulate well their capacity to react to potential difficulties, while driving. This heightened engagement fostered the development of advanced driving skills and strategies, enabling drivers to manage difficult situations more effectively. Consequently, the experience gained from handling complex tasks translated into improved overall driving competence and a greater ability to cope with unexpected challenges on the road.

Results also revealed that task complexity was positively correlated with risk due to several reasons. Firstly, crucial indicators such as the time of day and weather conditions significantly affect crash risk. Driving during night-time or in adverse weather conditions, such as rain or fog can exacerbate the challenges posed by complex tasks, further increasing the likelihood of crashes. Secondly, drivers could become overwhelmed by the demands of complex tasks, leading to reduced attention to the road and other traffic participants. This can result in delayed detection of critical events and inadequate responses. Additionally, complex tasks may require drivers to allocate more mental resources, causing them to divert attention from essential driving activities. For instance, interacting with in-vehicle technology or navigation systems can increase cognitive workload and lead to decreased focus on the primary task of driving.

Coping capacity was negatively correlated with risk, which means that as coping capacity increases, the crash risk decreases. This relationship can be explained by the fact that drivers with higher coping capacity are better equipped to handle complex and challenging driving situations. They can manage stress, make quicker and more accurate decisions and maintain better control over their vehicles, all of which contribute to safer driving. Consequently, their enhanced ability to cope with driving demands reduces the likelihood of crashes and other risky incidents, leading to a lower overall risk. Conversely, drivers with limited coping capacity may struggle to effectively manage complex tasks, leading to higher crash risk. Reduced coping capacity can manifest as slower reaction times, impaired judgment and difficulties in prioritizing information.

When looking into the relationship between the interaction of task complexity and coping capacity and its effect on risk, it was shown that the effect of task complexity on risk was greater than the impact of coping capacity on risk. Furthermore, a positive correlation of risk with the STZ indicators was identified in all phases, with the highest values being observed in the normal phase (i.e. STZ level 1), indicating that the latent variable risk could in fact be representing an inverse of risk, more like a normal driving. Lastly, models fitted on data from different phases of the on-road experiment validated that both real-time and post-trip interventions had a positive influence on risk compensation, increasing drivers' coping capacity and reducing dangerous driving behavior.

This study is not without limitations. Firstly, with regards to task complexity indicators, this work included a limited set of variables, such as weather conditions and time of day. For instance, variables on road type (i.e. highway, rural, urban) would need to be included for a complete picture of the role of task complexity on the risk expressed in terms of STZ. Similarly, a distinction per traffic volumes (i.e. high, medium, low) was not considered. Secondly, as per coping capacity, drivers’ demographic characteristics, such as education level or driving experience were not included in the analysis. Thirdly, the impact of participants' health and medical status was not taken into consideration.

Future research efforts could consider additional risk indicators. For instance, the presence of a passenger, the drug abuse, the alcohol consumption or the seat belt use constitute some of the high-risk factors that cause road crashes. As per further research directions, demographic characteristics such as educational level, or driving experience could be also taken into account. Furthermore, the experimental sample size could be strengthened, while comparisons among different countries or transport modes could be also made. Moreover, the developed models can be further exploited. For example, additional task complexity and coping capacity factors, such as road type, more personality traits and driving profiles could be utilized. Traffic density can profoundly affect driving complexity, influencing factors such as stress levels and reaction times. Thus, taking into consideration that drivers react differently under different circumstances with respect to traffic conditions (i.e. high, medium or low traffic volumes), it would be of great interest to investigate STZ speeding using traffic and driver data. Furthermore, data could be enhanced by including participants' health and medical parameters as well as additional measurements, such as electrocardiogram and electroencephalogram readings.

CONCLUSIONS

The aim of this study was to identify the interactions among road environment, vehicle state and driver behavior for the identification of the Safety Tolerance Zone (STZ). More specifically, the impact of task complexity and coping capacity on crash risk was examined. Towards that end, a naturalistic driving experiment was conducted, involving a total of 135 drivers aged 20-65 and a large database of 31,954 trips was collected and analysed.

In order to fulfil the aforementioned objective, exploratory analysis, such as Generalized Linear Models (GLMs) were developed and the most appropriate variables associated to the latent variable "task complexity" and "coping capacity" were estimated. Moreover, Structural Equation Models (SEMs) were used to explore how the model variables were inter-related, allowing for both direct and indirect relationships to be modeled. Given that SEM deals with latent concepts, and both task complexity and coping capacity are latent constructs, this approach was the most appropriate and constitutes the key component of the statistical analysis in this study. For this purpose, three latent variables were constructed, namely task complexity, coping capacity and risk.

Results showed that higher task complexity levels lead to higher coping capacity. This means that drivers, when faced with difficult conditions, tend to regulate well their capacity to apprehend potential difficulties, while driving. It was revealed task complexity and risk were positively correlated in all phases of the experiment, which means that increased task complexity relates to increased risk. On the other hand, coping capacity and risk found to have a negative relationship in all phases, which means that increased coping capacity relates to decreased risk. Overall, the interventions had a positive influence on risk, increasing the coping capacity of the operators and reducing the risk of dangerous driving behavior.

Understanding and modeling the interrelationship between task complexity, coping capacity and crash risk is vital for developing targeted interventions and countermeasures to enhance traffic safety and reduce crash risk on roadways. This includes improving road infrastructure, implementing appropriate signage and road markings, educating drivers about the impact of task complexity on their performance, and promoting the development of coping strategies to manage complex driving situations. Technological advancements in vehicle automation and driver assistance systems also play a role in mitigating crash risk by reducing the cognitive load associated with complex tasks and providing support to drivers in challenging driving conditions.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Eva Michelaraki, Amir Pooyan Afghari, Eleonora Papadimitriou, Constantinos Antoniou, Tom Brijs, George Yannis; data collection: Thodoris Garefalakis, Eva Michelaraki, Muhammad Adnan, Muhammad Wisal Khattak, Evita Papazikou, Rachel Talbot, Christelle Al Haddad; draft manuscript preparation: Thodoris Garefalakis, Eva Michelaraki, Muhammad Adnan, Muhammad Wisal Khattak, Evita Papazikou, Rachel Talbot, Christelle Al Haddad; analysis and interpretation of results: Thodoris Garefalakis, Eva Michelaraki, Muhammad Adnan, Muhammad Wisal Khattak, Amir Pooyan Afghari, Christelle Al Haddad, Eleonora Papadimitriou, Constantinos Antoniou, Tom Brijs, George Yannis. All authors reviewed the results and approved the final version of the manuscript.

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