Identifying the Impact of Task Complexity and Coping Capacity on Driving Risk - Comparison among Different Countries and Transport Modes

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ABSTRACT

Considering the significant influence of the human factor on safe driving behavior, the i-DREAMS project developed a 'Safety Tolerance Zone (STZ)' to define the precise boundary where self-regulated control can be maintained safely. This paper endeavors to model the inter-relationship among task complexity, coping capacity (i.e. vehicle and operator state) and crash risk. Towards that aim, 80 drivers participated in a naturalistic driving experiment carried out in three countries (i.e. Belgium, Germany and Portugal) and a large dataset of 19,000 trips was collected and analyzed. 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 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 to be modelled. Comparisons on the performance of such models, behaviors and driving patterns across different countries and transport modes were also provided. 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. 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. Thus, authorities may use data systems at population level to plan mobility and safety interventions, set up road user incentives, optimize enforcement and enhance community building on safe traveling.

Keywords: Task Complexity; Coping Capacity; Crash Risk; Generalized Linear Models; Structural Equation Models.

INTRODUCTION

Road safety is a critical concern worldwide, as road crashes claim the lives of millions and cause countless injuries each year. Factors such as human behavior, road design, vehicle safety features, environmental conditions, and socioeconomic disparities significantly influence the occurrence and severity of road crashes *(8)*. A substantial portion of these crashes can be attributed to driver behavior, making it a vital area of focus in traffic safety research *(11)*. Recognizing the significance of this issue, the European Union and the World Health Organization have set ambitious targets to reduce fatal traffic crashes by 50% from 2021 to 2030, with emerging technologies playing a pivotal role in achieving road safety improvements *(7)*.

Traffic circumstances, environmental conditions and driver's state are some of the risk factors that influence road safety. Despite advancements in technology and infrastructure, human error remains a significant contributor to traffic collisions *(12)*. However, the ongoing progress in autonomous vehicles holds promise for enhancing road safety by reducing reliance on human drivers *(5)*. Additionally, intelligent driving behavior monitoring systems, equipped with real-time interventions, have shown remarkable effectiveness in enhancing road safety. By combining the benefits of autonomous vehicles and intelligent monitoring systems, there is a strong potential for mitigating the impact of human error and creating a safer road environment for all road users.

Numerous studies have focused on understanding the impact of various factors on unsafe driving and have sought to develop suitable models for identifying risky driving behavior and establishing intervention frameworks within vehicles. While there have been proposals for various interventions during and post-trip the personalization of these interventions and a direct connection between real-time driving behavior and intervention activation remain areas for improvement.

The i-DREAMS project, funded by the European Commission Horizon 2020 initiative, aims to address these challenges by establishing, developing, testing, and validating a 'Safety Tolerance Zone' (STZ) to ensure safe driving behavior. By continuously monitoring risk factors associated with task complexity (e.g., traffic conditions and weather) and coping capacity (e.g., driver's mental state, driving behavior, and vehicle status), i-DREAMS aims to determine the appropriate level within the STZ and implement interventions to maintain drivers' operations within acceptable safety limits. The STZ comprises three levels: 'Normal', 'Dangerous', and 'Avoidable Accident'. The 'Normal' level indicates a low likelihood of a crash, while the 'Dangerous' level suggests an increased possibility of a crash without inevitability. The 'Avoidable Accident' level signifies a high probability of a crash, but it also allows sufficient time for drivers to take action and prevent it.

In line with the primary objective of the i-DREAMS project, this study aims to explore the dynamic interplay between task complexity and coping capacity, encompassing both vehicle state and operator state factors. For that purpose, data collected from a naturalistic driving experiment with a total sample of 80 drivers from Belgian truck drivers, German drivers and Portuguese bus drivers were collected and analyzed. Explanatory variables of risk and the most reliable indicators, such as time headway, distance travelled, speed, forward collision, time of the day (lighting indicators) or weather conditions were assessed.

The selection of both SEM and GLM for the implementation of the analyses was guided by the need to conduct a comprehensive investigation into the interaction between task complexity and coping capacity in the realm of road safety. SEM is a powerful tool for testing theoretical models, examining causal relationships, and analyzing latent variables, making it well-suited for exploring the intricate relationships among vehicle, operator, and context characteristics in influencing risk under various conditions *(4, 14)*. Furthermore, GLMs are effective in handling non-normal data, modeling categorical outcomes, addressing heteroscedasticity, and incorporating non-linear relationships, which is crucial for analyzing road safety data with diverse distributions and complex patterns *(1, 11).* By strategically employing both SEM and GLM, the research aimed to holistically explore the nuanced relationships between risk factors, driving behavior, and road safety outcomes, thereby contributing valuable insights to enhance road safety measures and reduce crash risk *(2, 9).* This integrative approach allowed for a robust and multifaceted analysis, offering a comprehensive understanding of the factors influencing road safety and paving the way for evidence-based interventions to promote safer driving practices.

The paper is structured in the following manner. At the beginning, a detailed introduction to the project and its general objective is highlighted with a literature review presented concerning the analysis of driving behavior utilizing statistical methods. The research methodology is outlined, including the explanantion of collecting the data and the theoretical foundations of the underlying models employed. Finally, the results of the study are presented, followed by significant conclusions regarding the relationship between key factors of task complexity and coping capacity on risk.

DATA DESCRIPTION

Experimental processing

A naturalistic driving experiment was carried out involving 80 drivers from Belgium, Germany and Portugal and a large database of 19,000 trips and 847,711 minutes was created to investigate the most prominent driving behavior indicators available, including speeding, headway, duration, distance and harsh events (i.e. harsh acceleration and harsh braking). The total number of drivers, trips and minutes per country and transport mode is presented in Figure 1 below:

Figure 1 Number of drivers, trips and minutes per country and transport mode

The on-road trials in i-DREAMS were designed based on several proven principles derived from previous literature focusing on testing interventions in order to assist drivers in maintaining the STZ. The on-road trials 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 and gamification) on driving behavior. Figure 2 provides an overview of the different phases of the experimental design of the i-DREAMS on-road study based on which the each SEM models was implemented.

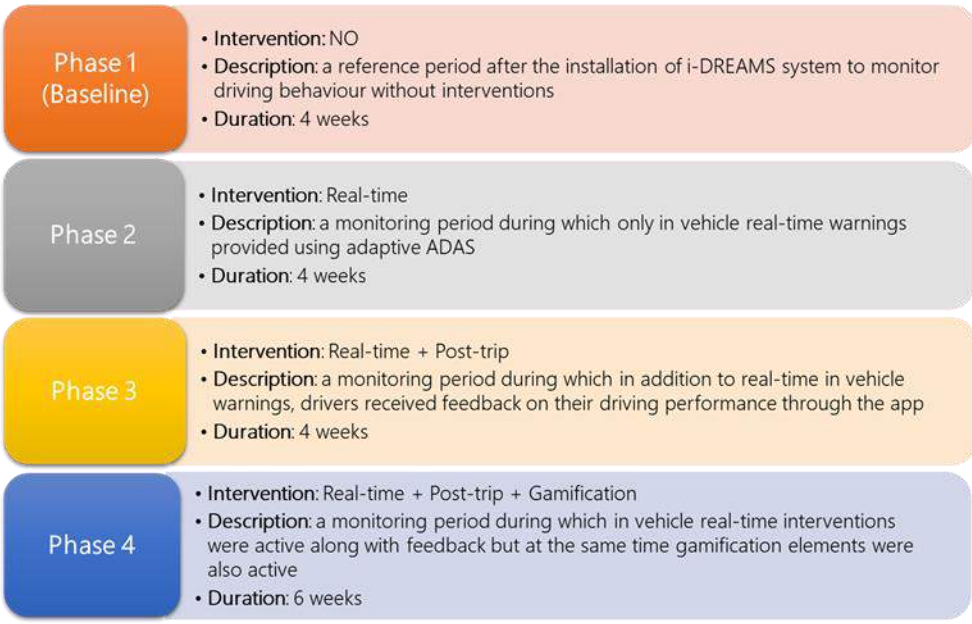

Figure 2 Overview of the different phases of the experimental design

Variables used to define task complexity and coping capacity

The most appropriate variables used in order to define task complexity and coping capacity (vehicle and operator state) along with the variables finally utilized to represent risk are shown in Figure 3.

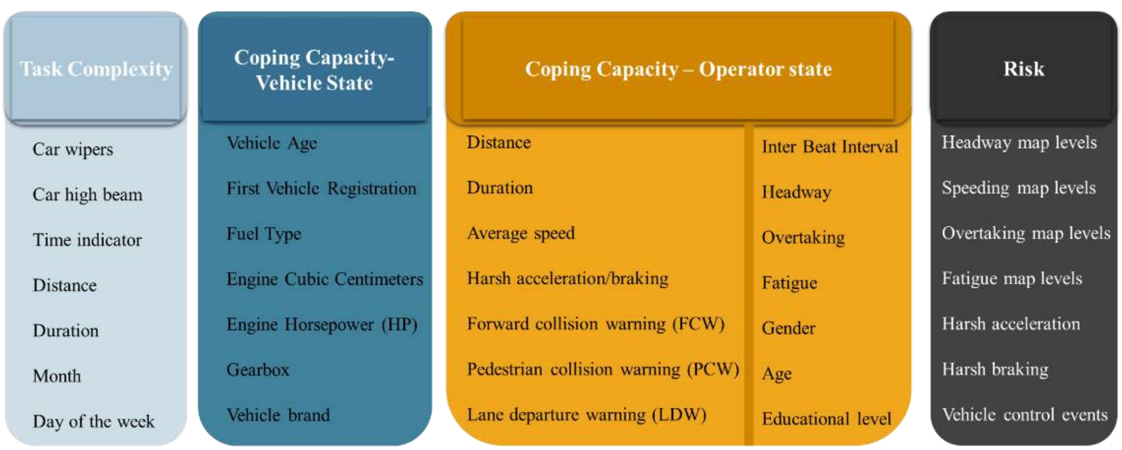

Figure 3 Variables for task complexity and coping capacity (vehicle and operator state) and risk

METHODS

Generalized Linear Models (GLMs)

In statistics, the 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 *(13).*

In a GLM, each outcome Y of the dependent variables is 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:

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

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:

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

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, McCullagh *(13)* 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. Other approaches, including Bayesian approaches and least squares fits to variance stabilized responses, have been developed.

Structural Equation Models (SEMs)

Structural Equation Modelling (SEM) or path analysis is a multivariate method used to test hypotheses regarding the influences among interacting observed (measurable) and unobserved variables or latent constructs *(10)*.

SEM consist of two components: a measurement model and a structural model *(2, 4)*. The measurement model is used to assess how well various observable exogenous variables can measure the latent variables, as well as the measurement errors associated with them. The structural model is used to investigate the relationships among the model variables, enabling the modeling of both direct and indirect linkages *(1)*. In this regard, SEMs distinguish themselves from regular regression techniques by deviating from direct relationships between variables.

The general formulation of SEM is as follows *(9)*:

$$\eta = \beta\eta + \gamma\xi + \varepsilon \quad (3)$$

In equation (3), η represents a vector of endogenous variables, ξ represents a vector of exogenous variables, β and γ are vectors of coefficients to be estimated, and ε represents a vector of regression errors.

The measurement models can be described as follows:

$$x = \Lambda x\xi + \delta, \text{ for the exogenous variables} \quad (4)$$
$$y = \Lambda y\eta + \zeta, \text{ for the endogenous variables} \quad (5)$$

In Equations (4) and (5), x and δ represent vectors associated with the observed exogenous variables and their errors, while y and ζ are vectors represent vectors associated with the observed endogenous variables and their errors. Λx, Λy are structural coefficient matrices that capture the effects of the latent exogenous and endogenous variables on the observed variables.

Model goodness-of-fit measures

In the context of model selection, model Goodness-of-Fit measures consist of an important part of any statistical model assessment. Several goodness-of-fit metrics are commonly used, including the goodness-of-fit index (GFI), the (standardized) Root Mean Square Error Approximation (RMSEA), the comparative fit index (CFI) and the Tucker-Lewis Index (TLI). Such criteria are based on differences between the observed and modelled variance-covariance matrices.

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 *(6):*

$$AIC= -2L(\theta)+ q \qquad (6)$$

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.

$$BIC= -2L(\theta)+ q \ln(N) \qquad (7)$$

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. The values of CFI range from 0 to 1, indicating a good fit for the model when the value exceeds 0.95 *(3)*. 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:

$$CFI = 1 - \frac{\max\,(x_H{}^2 - df_H, 0)}{\max\,(x_H{}^2 - df_H, x_I{}^2 - df_I)} \qquad (8)$$

where: x_H^2 is the value of x^2 and df_H is the degrees of freedom in the hypothesized model, and x_I^2 is the value of x^2 and d_{fI} is the degrees of freedom in the independence model.

The Tucker Lewis Index (TLI) considers the parsimony of the model. Therefore, if the fit indices of two models are similar, a simpler model (i.e. greater degrees of freedom) is chosen. TLI is an unstandardized value, so it can have a value less than 0 or greater than 1. It indicates a good fit for the model when the value exceeds 0.95. In general, 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:

$$TLI = \frac{\frac{x_I{}^2}{df_I} - \frac{x_H{}^2}{df_H}}{\frac{x_I{}^2}{df_I} - 1} \qquad (9)$$

Currently, one of the most widely used goodness-of-fit indices is the Root Mean Square Error Approximation (RMSEA). RMSEA measures the unstandardized discrepancy between the population and the fitted model, adjusted by its degrees of freedom (df). RMSEA is considered a “badness-of-fit measure” meaning that lower index values represent a better-fitting model. RMSEA index ranges between 0 and 1. Its value 0.05 or lower is indicative of model fit with observed data. P close value tests the null hypothesis that RMSEA is no greater than 0.05. If P close value is more than 0.05, the null hypothesis is accepted that

RMSEA is no greater than 0.05 and it indicates the model is closely fitting the observed data (RMSEA<0.05). The formula is represented as follows:

$$RMSEA = \sqrt{\frac{x_H{}^2 - df_H}{df_H(n-1)}} \qquad (10)$$

where: n is the sample size.

RESULTS

GLM Results

GLMs were employed to investigate the relationship of key performance indicator of speeding for Belgian truck drivers, German car drivers and Portuguese bus drivers. 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.

Belgian trucks

The first GLM investigated the relationship between the speeding and several explanatory variables of task complexity and coping capacity (operator state) in Belgium. 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, wipers and high beam, while for coping capacity - operator state, the variables used are distance traveled and harsh acceleration. It should be mentioned that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. The model parameter estimates are summarized in Table 1.

TABLE 1 Parameter estimates and multicollinearity diagnostics of the GLM

Variables	**Estimate**	**Standard Error**	**z-value**	**Pr(|z|)**	**VIF**
(Intercept)	3.668	0.043	85.768	< .001	-
Time indicator	0.908	0.078	11.683	< .001	1.882
Weather	0.009	4.217×10^{-4}	20.952	< .001	1.228
High beam – Off	-0.018	7.062×10^{-4}	-25.286	< .001	1.470
Harsh acceleration	2.661	0.181	14.689	< .001	1.013
Distance	-6.128×10^{-4}	7.273×10^{-5}	-8.426	< .001	1.678
Summary statistics					
AIC	17404.428				
BIC	17413.817				
Degrees of freedom	88377				

Based on Table 2, 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 0, wipers on coded as 1) 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. Taking into account the indicator of high beam (indicating lighting conditions; no high beam detected), a negative correlation was identified which means that when high beam was off - and, therefore, it was daytime - there were less speeding events. This finding comes in agreement with the previous argument with the indicator of time of the day that higher speeding events occur at night compared to the rest of the day.

Regarding the indicators of coping capacity - operator state, harsh accelerations had a positive relationship with the dependent variable (i.e. speeding), indicating that as the number of harsh acceleration increases, 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. Lastly, total distance travelled was negatively correlated with speeding which may be due to the fact that the longer a person drives, the more fatigued they may become, causing them to drive slower and more cautiously.

German cars

The second GLM investigated the relationship between the speeding and several explanatory variables of task complexity and coping capacity (vehicle and operator state) in Germany. For task complexity, the variables used are time indicator and high beam, for coping capacity - vehicle state, the variables used are type of fuel and vehicle age, while for coping capacity - operator state, the variables used are distance traveled, duration, harsh acceleration, drowsiness, gender and age. The model parameter estimates are summarized in Table 2.

TABLE 2 Parameter estimates and multicollinearity diagnostics of the GLM

Variables	**Estimate**	**Standard Error**	**z-value**	**Pr(|z|)**	**VIF**
(Intercept)	1.105	0.057	19.549	< .001	-
Duration	0.003	3.414×10^{-5}	73.366	< .001	1.262
Distance	5.735×10^{-4}	3.723×10^{-5}	15.404	< .001	1.029
Harsh acceleration	1.282×10^{-4}	1.974×10^{-6}	64.951	< .001	1.222
Fuel type - Petrol	0.219	0.010	21.446	< .001	1.328
Vehicle Age	3.162×10^{-5}	3.340×10^{-6}	9.469	< .001	1.277
Gender - Female	-0.275	0.021	-13.025	< .001	1.256
Age	-0.003	0.001	-2.289	0.022	1.076
Drowsiness	1.009×10^{-5}	2.656×10^{-6}	3.800	< .001	1.113
Time indicator	8.547×10^{-5}	1.925×10^{-6}	44.405	< .001	1.080
High beam - On	0.817	0.059	13.963	< .001	1.073
Summary statistics					
AIC	127971.813				
BIC	127981.881				
Degrees of freedom	174299				

Based on Table 3, it can be observed that all explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity (VIF<5). With regards to the coefficients, it was revealed that the indicators of task complexity, such as time and high beam (indicating lighting conditions; no high beam detected) were positively correlated with speeding. Regarding the indicators of coping capacity – vehicle state, such as fuel type and vehicle age were positively correlated with speeding. Furthermore, it was demonstrated that indicators of coping capacity – operator state, such as harsh accelerations, distance, duration and drowsiness had a positive relationship with the dependent variable (i.e.

speeding), indicating that as the values of the aforementioned independent variables increases, 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.

Portuguese buses

The third GLM investigated the relationship between speeding and several explanatory variables of task complexity and coping capacity (vehicle and operator state) in Portugal. More specifically, for task complexity, the variable used is time indicator while for coping capacity - operator state, the variables used are distance traveled, harsh acceleration, harsh braking and fatigue. It should be mentioned that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. The model parameter estimates are summarized Table 3.

TABLE 3 Parameter estimates and multicollinearity diagnostics of the GLM

Variables	**Estimate**	**Standard Error**	**z-value**	**Pr(|z|)**	**VIF**
(Intercept)	3.441	0.020	168.858	< .001	-
Time indicator	0.164	0.008	21.306	< .001	1.002
Harsh braking	0.294	0.082	3.594	< .001	1.051
Harsh acceleration	0.490	0.112	4.371	< .001	1.052
Fatigue	-0.095	0.008	-12.527	< .001	1.378
Distance	0.010	1.038×10^{-4}	99.797	< .001	1.379
Summary statistics					
AIC	153657.374				
BIC	153668.223				
Degrees of freedom	380656				

It can be observed that all explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity (VIF<5). With regard to the coefficients, it was revealed that the indicators of task complexity, such as time indicator was positively correlated with speeding. Time indicator 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. Regarding the indicators of coping capacity - operator state, distance and harsh events (i.e. harsh acceleration and harsh braking) had a positive relationship with the dependent variable (i.e. speeding), indicating that as the total distance traveled and the number of harsh events increases, speeding also increases. Lastly, fatigue was negatively correlated with speeding which implies that the more fatigued the driver is, the slower and more cautiously they drive.

SEM Results

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 stages of the STZ).

Belgian trucks

The results for each phase are shown in Figure 4 below. The latent variable risk is measured by means of the STZ levels for acceleration (level 1 'normal driving' used as the reference case), with negative correlations of risk with the STZ indicators. The negative sign shows that the latent variable risk could in fact be representing an inverse of risk, more like a normal driving. The structural model between the latent variables shows some interesting findings: first, task complexity and coping capacity are inter-related with a positive correlation. 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.

Task complexity increase is associated with higher (risk) normal driving (lower risk), which is not intuitive. Although the initial assumption was that task complexity would increase risk or decrease normal driving, once its effect is moderated by that of coping capacity the opposite is the case. It is noted however that the task complexity latent variable is measured by environmental indicator (i.e. rainy weather) and situational indicator (i.e. speed) which are known to induce compensatory behaviors by drivers, in particular expressed as reduced speed during the more demanding conditions.

At the same time, coping capacity is negatively associated with normal driving or inverse of risk, again an interesting finding. It could be assumed that higher coping capacity might reduce risk or improve normal driving but this is not the case here. Furthermore, the coping capacity indicators in our sample include static demographic and self-reported behavior indicators and therefore are more representative of driver personality and general driving styles, and less so of the real-time operator state during the experiment. For instance, indicators related to the level of sleepiness, fatigue or distraction were either not available or not significant in this model. Therefore, it can be concluded that younger, more confident truck drivers exhibited (higher risk) lower normal driving in this experiment, in terms of exceeding the STZ acceleration boundaries, without however taking into account the variations of their state during these trips.

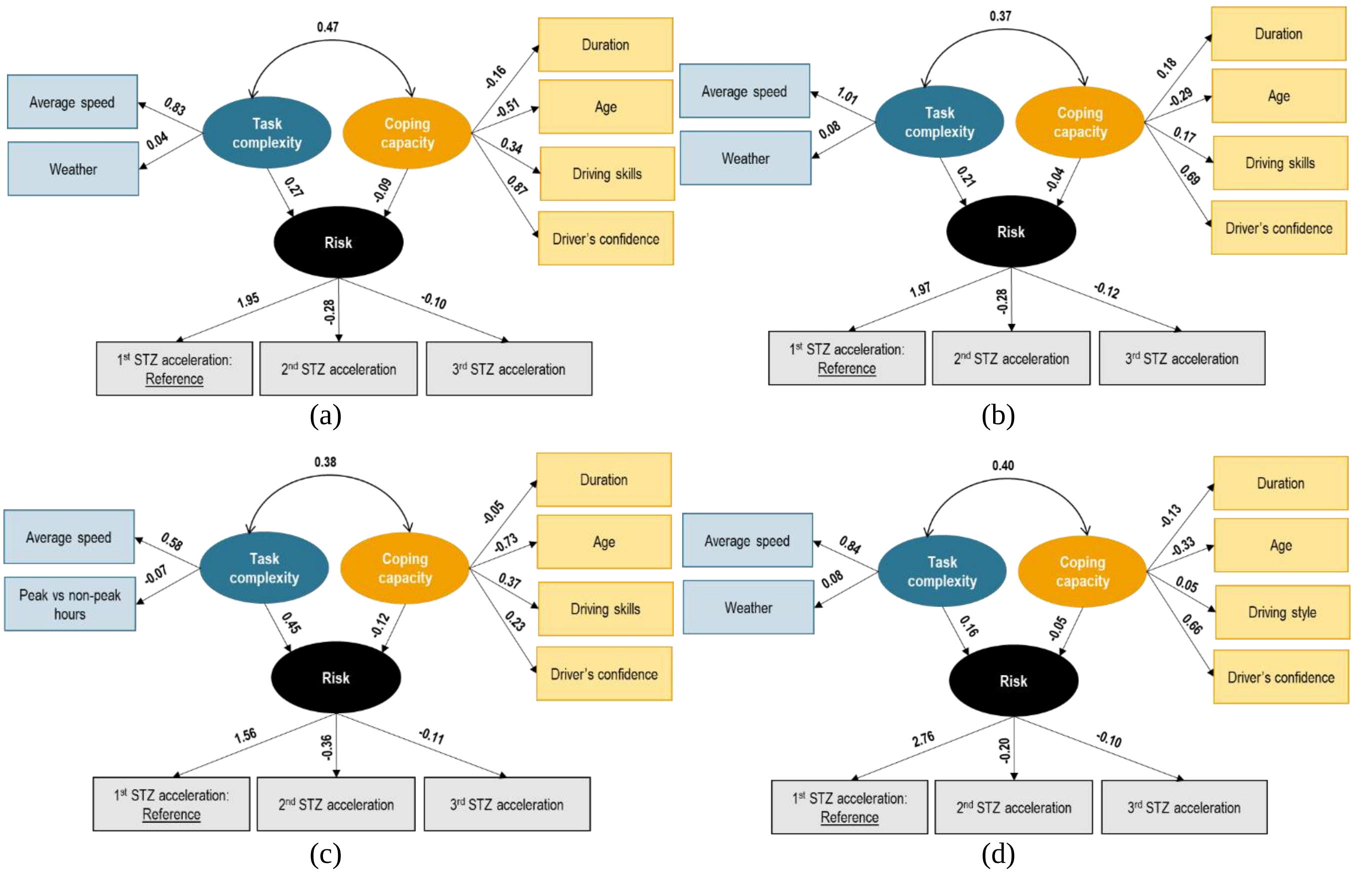

Figure 4: Results of SEM on risk – Belgian truck drivers – experiment phase 1 (a), 2 (b), 3 (c), 4 (d)

It is observed that the relationships among risk, task complexity and coping capacity are consistent between the different phases (except for phase 3 where coping capacity and risk have positive relationship). In particular, in phase 3, the structural relationship between coping capacity and (inverse) risk changes to a positive coefficient. This finding may not be directly interpreted, but it is possible that the presence of real time and post trip i-DREAMS interventions in phase 3 lead to a different interaction between the latent variables coping capacity and risk, which would need additional indicators available in order to draw conclusions. Also, the magnitude of the correlation between latent variables coping capacity and task complexity reduces to extremely small value.

The loading of 'trip duration' in phase 2 changes to positive sign which shows an improvement in the coping capacity of drivers in the presence of real-time interventions. However, in the later phases 3 and 4, this trend is back as the phase 1. The loadings of the observed proportions of the STZ of acceleration are consistent between the different phases (The loadings of 2nd STZ level have consistently higher negative sign across all phases while the loadings of 3rd STZ level have consistently lower sign across all phases). The loading of 1st STZ level becomes notably higher in the 4th phase of the experiment. This may indicate that drivers tend to have normal driving in 4th phase in the presence of all interventions.

Looking at the observed risk factors, it was demonstrated that for harsh accelerations in Belgian trucks, the correlation of coping capacity and task complexity was in general positive along the same magnitude for all phases.

German cars

To begin with, risk is measured by means of the STZ levels for speeding (level 1 'normal driving' used as the reference case; level 2 refers to 'dangerous driving', while no incidents with regards to level 3 'avoidable accident driving' were found). In particular, positive correlations of risk with the STZ indicators were found. It should be noted that the identified model indicated that level 3 of speeding variable does not have significant loading in the measurement model for the latent variable risk and thus, this level was not included in the final model. Level 1 and level 2 of speeding (or STZ 1 and STZ 2 indicators) have positive loadings in relationship to the latent variable Risk, respectively.

The latent variable task complexity is measured by means of the environmental indicator of "ME_AWS_time_indicator_median" (indicating time of the day). It should be noted that based on the definition of task complexity, road layout, time, location, traffic volumes and weather variables should be included in the analysis. However, road type (i.e. urban, rural, highway), location, traffic volumes (i.e. high, medium, low) and weather were not available in German dataset. Thus, only the time indicator was able to be used in the models applied. To that aim, exposure indicators, such as trip duration and distance traveled 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 state indicators, such as "VehicleAge" (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 "Age" (indicating the age of the driver) are included in the SEM applied.

The structural model between the latent variables shows some interesting findings: first, task complexity and coping capacity are inter-related with a positive correlation (regression coefficient=0.03) – which reduces in magnitude as the driver's progress from phases 1 and 2 though phases 3 and 4. 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 structural model 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=2.19). 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=-0.05).

It is observed that the measurement equations of task complexity and coping capacity are consistent between the different phases. At the same time, the loadings of the observed proportions of the STZ of speeding are consistent between the different phases. The structural model between task complexity and inverse risk (normal driving) are positively correlated among the four phases, while coping capacity and risk found to have a negative relationship in all phases of the experiment.

In Germany, the model for speeding revealed a positive correlation of task complexity and coping capacity, but with the largest correlation on phase 2 of the experiment, where real-time warnings were introduced. At the end of the experiment (phase 4), coping capacity was found to have its largest correlation with risk, while task complexity had its greatest loading during phase 3 of the experiment.

The results for all phases are shown in Figure 5 below.

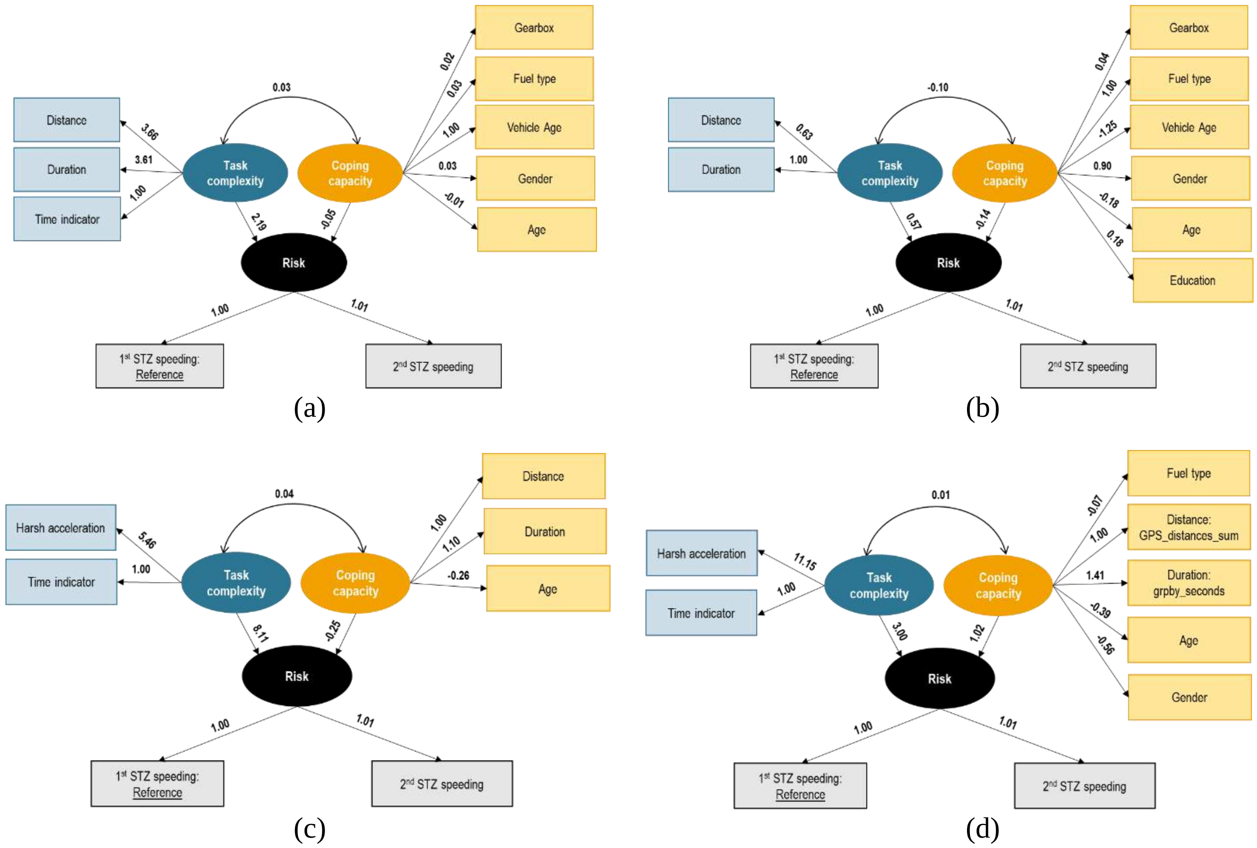

Figure 5: Results of SEM on risk – German car drivers – experiment phase 1 (a), 2 (b), 3 (c), 4 (d)

Portuguese buses

Risk is measured by means of the STZ levels for headway (level 1 'normal driving' used as the reference case; level 2 refers to 'dangerous driving', while level 3 refers to 'avoidable accident driving'. In particular, negative correlations of risk with the STZ indicators were found.

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

Moreover, it is shown that the latent coping capacity is measured by means of operator state indicators, such as average speed, distance, harsh acceleration and harsh braking. It should be noted that vehicle state indicators, such as vehicle age, gearbox, fuel type or socio-demographic characteristics were not provided.

The structural model between the latent variables shows some interesting findings: first, task complexity and coping capacity are inter-related with a positive correlation (regression coefficient=0.96) – which reduces in magnitude as the driver's progress from phases 1 and 2 though phases 3 and 4. 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 structural model 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=5.36). 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=-5.02).

The results for all phases are shown in Figure 6 below. It is observed that the measurement equations of task complexity and coping capacity are consistent between the different phases. The structural model between task complexity and inverse risk (normal driving) are positively correlated in phases 1, 3 and 4, while a negative correlation of phase 2 was identified. At the same time, coping capacity and risk found to have a negative relationship in all phases of the experiment.

In Portugal, task complexity was positively associated with the latent variable risk, which was defined by different levels of headway. The higher the complexity, the higher the chance to drive normally and more carefully. On the other hand, coping capacity was negatively associated with risk (or normal driving) which implied that higher coping capacity might encourage normal driving and reduce risk. Task complexity and coping capacity were inter-related with a positive correlation – which reduced in magnitude as the driver's progress from phase 1 though phase 4. Similar patterns of professional drivers (in terms of loadings and signs among phases for Belgian truck and Portuguese bus drivers) were observed.

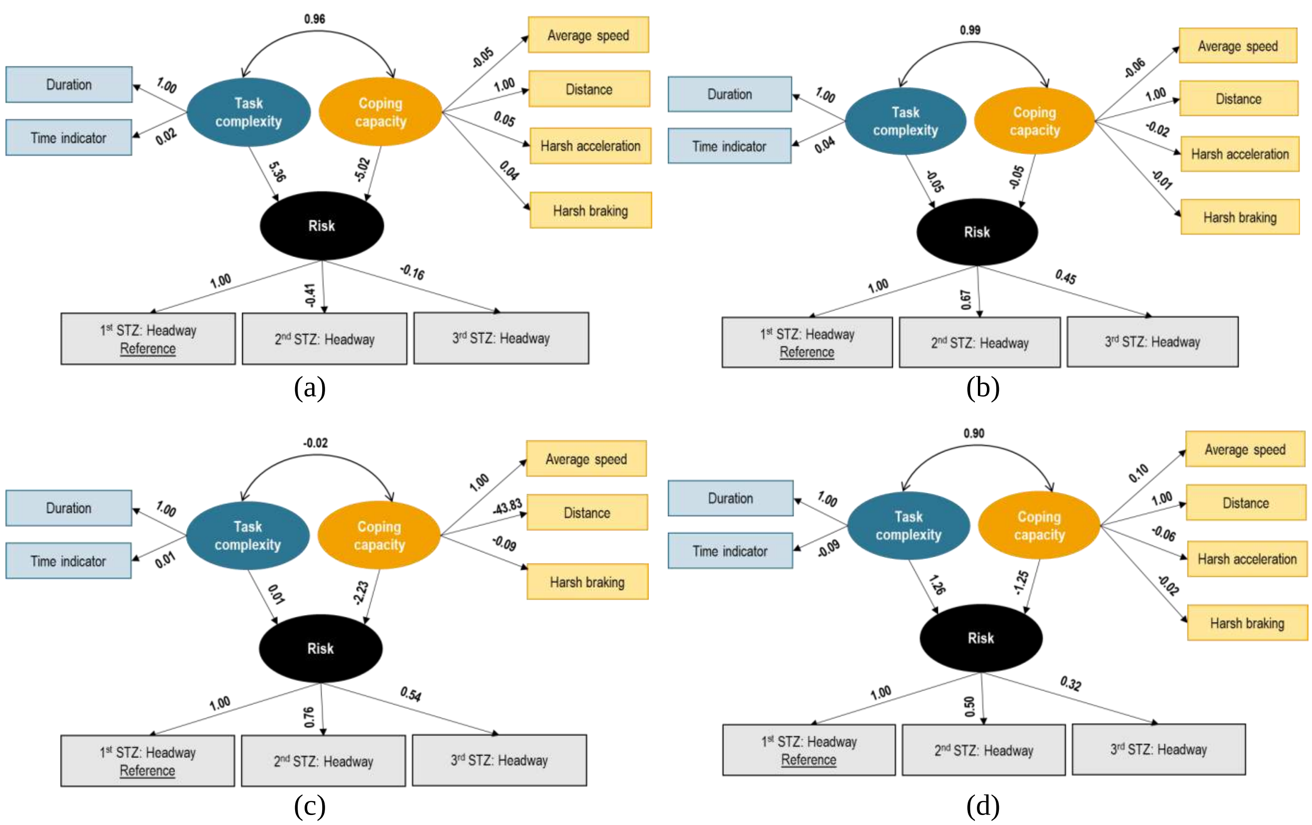

Figure 6: Results of SEM on risk – Portuguese bus – experiment phase 1 (a), 2 (b), 3 (c), 4 (d)

Table 4 summarizes the model fit of SEM applied for different counties (Germany, Belgium, Portugal), transport modes (cars, trucks, buses) and experimental phases.

TABLE 4 Model Fit Summary for different counties, transport modes and experimental phases

Model Fit measures	Phase 1	Phase 2	Phase 3	Phase 4
Belgian (Trucks)				
AIC	2730.212	6417.821	3177.783	6089.699
BIC	2730.234	6417.839	3177.802	6089.713
CFI	0.921	0.813	0.882	0.843
TLI	0.881	0.719	0.778	0.764
RMSEA	0.062	0.088	0.064	0.077
Hoelter's critical N (α = .05)	386	197	372	256
Hoelter's critical N (α = .01)	456	232	439	302
German (Cars)				
AIC	813827.574	676463.527	282420.347	525983.888
BIC	814118.257	676746.197	282625.175	526243.996
CFI	0.981	0.960	0.996	0.978
TLI	0.974	0.944	0.993	0.966
RMSEA	0.079	0.117	0.059	0.100
Hoelter's critical N (α = .05)	0.961	0.920	0.983	0.943
Portugal (Buses)				
AIC	3.328×10+6	1.699×10+6	1.511×10+6	1.594×10+6
BIC	3.328×10+6	1.699×10+6	1.511×10+6	1.595×10+6
CFI	0.983	0.985	0.998	0.964
TLI	0.974	0.978	0.997	0.946
RMSEA	0.053	0.052	0.019	0.051
Hoelter's critical N (α = .05)	0.985	0.986	0.998	0.986
Hoelter's critical N (α = .01)	533.123	556.489	4284.444	582.268

DISCUSSION

As task complexity increased, drivers may experience greater cognitive load and divided attention, potentially leading to decreased situational awareness and slower response times. These factors can impair decision-making abilities and increase the likelihood of errors or collisions.

Results indicated that higher task complexity was associated with an increased crash risk due to several reasons. Firstly, drivers could probably 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. Secondly, 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.

Conversely, drivers with limited coping capacity may struggle to manage effectively complex tasks, leading to higher crash risk. Reduced coping capacity can manifest as slower reaction times, impaired judgment, and difficulties in prioritizing information. In situations where the demands of the driving task exceed a driver's coping capacity, there is an increased likelihood of errors, misjudgments, and collisions.

It is worth noting that the relationship between task complexity and risk, as well as coping capacity and risk, may depend on the specific context and the type of task or activity involved. In general, higher task complexity may increase the potential for errors or crashes, as it can lead to greater cognitive or physical demands on the individual performing the task. However, it is also possible that increased experience or training can help to mitigate the risk associated with higher task complexity. Similarly, a higher coping capacity may help to reduce the risk of crashes or errors, as it can provide individuals with the resources or strategies needed to manage effectively challenging or stressful situations. However, the effectiveness of coping strategies may depend on the specific context and the individual's ability to apply them in real-world situations. Overall, it is important to consider the specific factors and context involved when assessing the relationship between task complexity, coping capacity, and risk.

The developed models presented can be further exploited by researchers and practitioners. Additional task complexity and coping capacity factors, such as road type, more personality traits and driving profiles could be utilized for example. Furthermore, data could be enhanced by including additional measurements such as electrocardiogram and electroengephalogram readings, traffic conflicts and transport emissions. Finally, additional methodologies such as imbalanced learning and models taking into account unobserved heterogeneity could be explored for the understanding of the relationship between task complexity, coping capacity and crash risk.

CONCLUSIONS

The ultimate goal of the analyses in this work was to identify the impact that the balance between task complexity and coping capacity has on the risk of a crash. To that end, 80 drivers participated in a naturalistic driving experiment carried out in three countries (i.e. Belgium, Germany and Portugal) and a large dataset of 19,000 trips was collected and analyzed.

In order to fulfil the aforementioned objective, exploratory analysis, such as GLMs were developed and the most appropriate variables associated to the latent variable "task complexity" and "coping capacity" were estimated. Moreover, SEMs were used to explore how the model variables were inter-related, allowing for both direct and indirect relationships to be modelled.

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 inverse 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 inverse 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.

All in all, the inter-relationship between driving task complexity, coping capacity, and crash risk is a multifaceted and crucial area of study in traffic safety research. The interplay between driving task complexity and coping capacity directly impacts crash risk, as drivers who are overwhelmed by high task complexity and have limited coping capacity may experience reduced situational awareness, slower reaction times, impaired decision-making, and increased likelihood of errors or collisions. Conversely, drivers with better coping capacity can effectively handle complex driving tasks, mitigate risks, and maintain safer driving behaviors.

Understanding and modeling this inter-relationship 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 our 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. Lastly, technological advancements in vehicle automation and driver assistance systems can 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: Study conception and design: Eva Michelaraki, Christos Katrakazas, Tom Brijs, George Yannis; data collection: Stella Roussou, Thodoris Garefalakis, Eva Michelaraki, Muhammad Adnan, Muhammad Wisal Khattak; draft manuscript preparation: Stella Roussou, Thodoris Garefalakis, Eva Michelaraki, Muhammad Adnan, Muhammad Wisal Khattak; analysis and interpretation of results: Stella Roussou, Thodoris Garefalakis, Eva Michelaraki, Muhammad Adnan, Muhammad Wisal Khattak, Tom Brijs, George Yannis. All authors reviewed the results and approved the final version of the manuscript.

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