Improving Driver Safety Tolerance Zone through Holistic Analysis of Road, Vehicle and Behavioural Risk Factors: A Comparison using Driving Simulator and Naturalistic Data

Eva Michelaraki
PhD, Research Associate
Department of Transportation Planning and Engineering
National Technical University of Athens, Athens, Greece, GR15773
*Email: evamich@mail.ntua.gr

George Yannis
Professor
Department of Transportation Planning and Engineering
National Technical University of Athens, Athens, Greece, GR15773
Email: geyannis@central.ntua.gr

Word Count: 6,493 words + 4 tables (250 words per table) = 7,493 words

Submitted: July 31, 2025
*Corresponding Author

ABSTRACT

Headway, the time or distance between two vehicles, is a critical factor in road safety, particularly in relation to rear-end collisions. This study aims to improve the Driver Safety Tolerance Zone (STZ) by examining the combined influence of road environment, vehicle state and driver behaviour through a holistic approach. The STZ represents the dynamic balance between task complexity and coping capacity and is designed to capture transitions between safe, risky and potentially hazardous driving phases. To achieve this, data were collected from a naturalistic driving experiment involving 135 and a driving simulator study with 55 participants. Generalized Linear Models (GLMs) were used to identify the key explanatory variables of headway events, while Structural Equation Models (SEMs) explored the latent constructs of task complexity, coping capacity and risk. Results indicated that task complexity had a positive correlation with crash risk, especially during night-time and adverse weather conditions. Conversely, coping capacity, reflected through behavioural indicators, was negatively associated with risk, highlighting drivers' ability to compensate under challenging conditions. A positive relationship was observed between task complexity and coping capacity, implying that drivers respond to more demanding situations by increasing their engagement. This study demonstrated the effectiveness of the STZ concept as a comprehensive model for interpreting driving behaviour across diverse conditions. The benefits of integrating behavioural, environmental and vehicle-related data to enhance traffic safety were also highlighted. The outcomes of this holistic approach may provide meaningful guidance for policymakers, encouraging data-informed safety strategies and the adoption of connected, user-oriented technologies.

Keywords: Safety Tolerance Zone; Task Complexity; Coping Capacity; Crash Risk; Structural Equation Models.

INTRODUCTION

One of the primary contributors to traffic collisions is insufficient headway, the gap between two vehicles, which, when too narrow, restricts the following driver's ability to respond to sudden braking by the vehicle ahead *(1)*. This distance can be quantified in terms of both time and space *(2)*. Maintaining an adequate headway is essential for managing both the physical and cognitive demands of driving, as it provides drivers with sufficient time to react to abrupt changes in traffic. Having this time reduces stress and cognitive load, thereby enhancing situational awareness. In contrast, limited headway heightens crash risk by demanding faster reflexes and greater concentration, which can increase stress and lead to faster onset of fatigue.

Driver workload, often considered a mediating variable between task difficulty and performance, reflects the driver's capacity to meet task demands *(3)*. An increase in perceived workload typically prompts compensatory behaviour, such as reducing speed or increasing headway, to manage more challenging driving conditions. Research has shown that increased workload is often associated with decreased speed and extended headway, as drivers attempt to simplify the task. Additionally, variability in speed and headway tends to rise with higher workload *(4)*, indicating reduced control over longitudinal vehicle dynamics. Lateral position variability has also been observed to both increase and decrease depending on the source of workload *(5)*. These fluctuations can raise crash risk, particularly if they result in lane departures or dangerously short headways. Moreover, if drivers fail to adjust adequately to higher workload or task complexity, their reaction time to hazards may increase, leaving insufficient time to avoid a collision.

The ultimate goal of the current work is to develop a context-aware 'Safety Tolerance Zone' for both simulator and naturalistic driving experiments. This STZ defines the point at which self-regulated driving remains within safe boundaries *(6)*. It represents the zone where the demands of the driving task (i.e. task complexity) are balanced with the driver's ability to manage those demands (i.e. coping capacity). The STZ consists of three distinct phases: normal driving, danger and avoidable accident. The normal driving phase reflects conditions in which the likelihood of a crash is low and the driver is effectively adapting their behaviour to meet task requirements. The danger phase emerges when changes in conditions indicate an increased crash risk, although a collision is not yet inevitable. The STZ transitions into this phase when real-time measurements detect risk-elevating changes. The final phase, the avoidable accident phase, occurs when a crash scenario is unfolding, but there is still an opportunity for the driver to take corrective action. In this phase, the urgency for intervention is heightened; without timely responses, a crash becomes highly likely.

Within the above framework, this research constitutes a holistic approach to improve driver STZ through the analysis of road, vehicle and behavioural risk factors. The aim of this study was to determine the interactions among road, vehicle and driver risk factors for the identification of the STZ. More specifically, the impact of task complexity and coping capacity (in terms of both vehicle and driver state factors) on crash risk was investigated. For that purpose, a large dataset spanning four months from both simulator and naturalistic driving experiment was exploited.

The structure of the paper is as follows: At the beginning, the study's motivation and objectives, along with an explanation of the STZ concept are presented. Next, a comprehensive overview of the data collection process is provided. Then, the research methodology is described, including the theoretical basis of the models employed. Moreover, the analysis results are presented, followed by a detailed discussion of the main conclusions. Finally, suggestions and directions for future research are highlighted.

DATA OVERVIEW

To fulfill the aim of this work, a simulator experiment was conducted with 55 participants, complemented by a naturalistic driving experiment, involving 135 drivers. Furthermore, data from 31,954 on-road and 165 simulator trips were collected and analyzed. Key explanatory variables related to risk and the most reliable indicators of task complexity (e.g. weather, time indicator), coping capacity - vehicle state (e.g. gearbox, vehicle age, fuel type) and coping capacity - driver state (e.g. headway, speed, harsh brakings) were evaluated. **Figure 1** presents the conceptual framework used for risk prediction, focusing on task complexity and coping capacity.

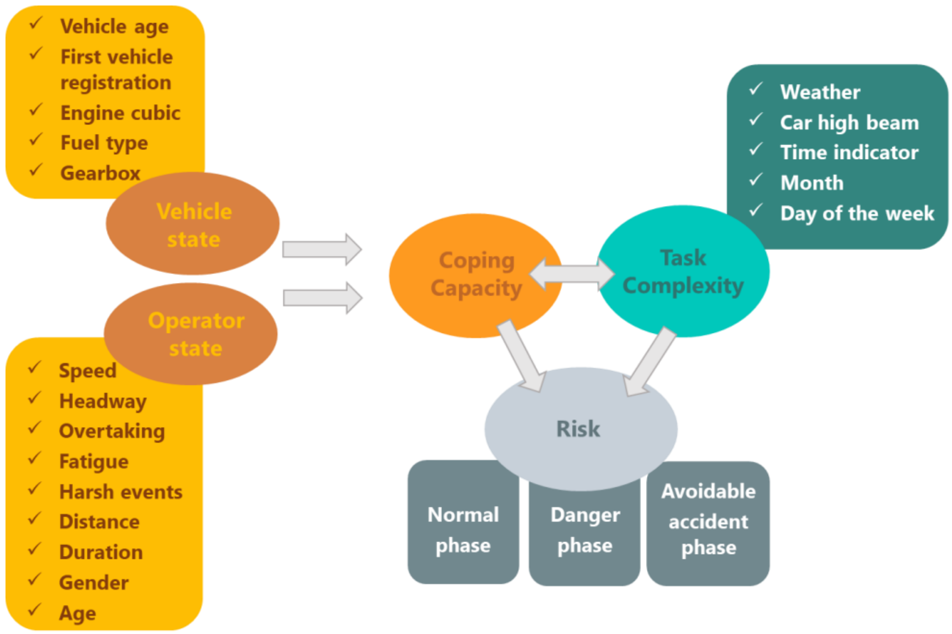

Figure 1 Conceptual framework for risk prediction in function of task complexity and coping capacity

In relation to the STZ concept, a comprehensive system of monitoring technologies was deployed across three aspects: driver, environment and vehicle. Vehicles were equipped with Mobileye and CardioDashcam systems to continuously monitor the road environment and driving behaviour. For monitoring the driver's physiological state and detecting drowsiness or sleepiness, CardioWheel and the PulseOn wearable were used. Vehicle-related indicators, such as GPS position, inertial data and engine parameters, were collected via OBD-II and Fleet Management System interfaces, contributing to the evaluation of coping capacity in terms of vehicle state. An intervention device, connected to the CardioGateway, provided real-time visual and auditory alerts based on the driver's current STZ, while a smartphone application monitored key performance indicators, such as speeding, harsh events or mobile phone use while driving. The technology illustrated in **Figure 2** captures indicators related to the driver, environment and vehicle state, which were used to assess task complexity and coping capacity.

Figure 2 Technologies used to measure driver, environment and vehicle state

METHODS

As part of this research, Generalized Linear Models (GLM) were implemented to examine the the key correlations among observed metrics and identify the effect of task complexity and coping capacity on specific driving performance parameters. Moreover, Structural Equation Models (SEM) were performed to identify the impact between latent and observable variables of task complexity and coping capacity with crash risk. SEM constituted the key component of this study as it can be used to explore how the model variables are inter-related, allowing for both direct and indirect relationships to be modelled. In the present analysis, task complexity, coping capacity and risk are the unobserved variables which are estimated from specific parameters.

Generalized Linear Models (GLM)

Generalized Linear Model (GLM) is an adaptable extension of traditional linear regression that accommodates response variables with error distributions beyond the normal distribution. This framework broadens linear regression by introducing a link function to connect the linear predictor to the response variable and by allowing the variance of each observation to vary as a function of its expected value *(7)*.

In a GLM, each observed outcome Y of the dependent variables is assumed to arise from a distribution belonging to the exponential family, a broad category that encompasses distributions such as normal, binomial, Poisson and gamma *(8)*. The expected value, μ, of the response variable is modelled as a function of the independent variables X, typically through the following equation:

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

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:

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

While it is advantageous for the variance function V to arise from a distribution within the exponential family, it is not strictly required; the variance may simply be modelled as a function of the predicted value.

The unknown parameters, β, in the model are commonly estimated using methods such as maximum likelihood estimation, maximum quasi-likelihood, or Bayesian approaches. A foundational aspect of the development of the GLM was the extension of the normal distribution, traditionally used in linear regression, to the broader class of exponential family distributions. This generalization was formally introduced by Collins et al. *(9)*. To illustrate, consider a single random variable y, where the probability mass function (for discrete variables) or probability density function (for continuous variables) is defined in terms of a parameter θ. The distribution is said to belong to the exponential family if it can be expressed in the following form:

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

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:

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

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. Moreover, any additional parameters beyond the primary parameter of interest θ are considered nuisance parameters, which are incorporated into the functions a, b, c and d and are treated as if their values are known. It is also important to address multicollinearity in regression models, which arises when two or more independent variables are highly correlated. This issue can be evaluated using the Variance Inflation Factor (VIF), a diagnostic measure that quantifies the extent of multicollinearity. A commonly used threshold is a VIF value below 5 (VIF<5), indicating that the variable is suitable for inclusion in the model. However, in some cases, VIF values below 10 may still be considered acceptable depending on the context and field of application.

Structural Equation Models (SEM)

Structural Equation Modelling (SEM), also known as path analysis, is a multivariate statistical technique used to test hypotheses about the relationships among interacting observed and latent (unobserved) variables *(10)*. In this context, observed variables are directly measurable, while latent variables represent theoretical constructs that cannot be measured directly. SEM is composed of two main parts: the measurement model and the structural model *(11)*. The measurement model evaluates how effectively observed exogenous variables represent the latent constructs and accounts for any measurement errors. In contrast, the structural model explores the causal relationships between variables, allowing for both direct and indirect effects to be modelled. This dual structure enables SEM to go beyond standard regression methods, which typically assume only direct relationships between variables.

The general formulation of SEM, as outlined by Washington et al. *(12)*, is as follows:

$$\eta = \beta\eta + \gamma\xi + \varepsilon \qquad (5)$$

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 (Chen, 2007):

$$x = \Lambda x\xi + \delta, \text{ for the exogenous variables} \qquad (6)$$
$$y = \Lambda y\eta + \zeta, \text{ for the endogenous variables} \qquad (7)$$

In equations (6) and (7), x and δ denote vectors corresponding to the observed exogenous variables and their associated measurement errors, respectively, while y and ζ represent vectors for the observed endogenous variables and their corresponding errors. The matrices Λx and Λy are structural coefficient matrices that quantify the influence of latent exogenous and endogenous variables on the observed variables. It should be noted that prior to estimating the SEM, an Exploratory Factor Analysis (EFA) was also conducted using principal axis factoring with varimax rotation to determine the structure of latent constructs. Two latent variables (i.e. task complexity and coping capacity) were defined based on observed indicators. Items with factor loadings ≥ 0.40 were retained for their respective constructs. The EFA supported the assignment of variables to the two constructs, which were then used in the SEM framework.

Goodness-of-Fit Measures

In model selection, evaluation metrics play a crucial role in assessing the quality and performance of statistical models. Several widely used goodness-of-fit measures include the Goodness-of-Fit Index (GFI), the (Standardized) Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI). These metrics evaluate how well the model reproduces the observed data by comparing the observed and estimated variance-covariance matrices. Additionally, the Akaike Information Criterion (AIC) is commonly employed to compare models with different combinations of explanatory variables, as it balances model fit with model complexity by penalizing the inclusion of additional parameters *(13)*.

$$AIC = -2L(\theta) + q \quad (8)$$

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.

$$BIC = -2L(\theta) + q \ln(N) \quad (9)$$

It is worth mentioning that the AIC and BIC are commonly used metrics for evaluating model performance while accounting for model complexity. Both criteria incorporate a measure of model fit along with a penalty term that increases with the number of estimated parameters, thereby discouraging overfitting. Lower values of AIC or BIC indicate a more parsimonious and better-fitting model.

The Comparative Fit Index (CFI) is based on the noncentral x^2 distribution and assesses model fit by comparing the hypothesized model to a baseline (independence) model. CFI values range from 0 to 1, with values above 0.95 indicating a good model fit. Generally, a CFI value exceeding 0.90 (CFI>0.90) is considered acceptable and reflects a strong overall model fit. The formula for calculating the CFI is given as follows:

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

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), also known as the non-normed fit index, accounts for model parsimony by incorporating the model's degrees of freedom into the assessment. As a result, when two models exhibit similar fit indices, the TLI favors the more parsimonious model, that is, the one with more degrees of freedom. Unlike some standardized indices, the TLI is not bounded strictly between 0 and 1 and it can occasionally produce values less than 0 or greater than 1. Nonetheless, TLI values exceeding 0.90 (TLI>0.90) are commonly interpreted as indicators of a very good model fit. The formula is given 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.

One of the most commonly used goodness-of-fit indices today is the Root Mean Square Error of Approximation (RMSEA). RMSEA evaluates how well a model, with unknown but optimally chosen parameter estimates, would fit the population's covariance matrix. It measures the unstandardized discrepancy between the observed data and the model, adjusted for model complexity through the degrees of freedom. RMSEA values range from 0 to 1, with values of 0.05 or lower generally indicating a good fit to the data. Additionally, the p-close value tests the null hypothesis that RMSEA is less than or equal to 0.05. If the p-close value exceeds 0.05, the null hypothesis is accepted, suggesting that the model closely fits the data (RMSEA<0.05). The formula is given as follows:

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

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. The adjusted goodness of fit index (AGFI) corrects the GFI, which is affected by the number of indicators of each latent variable. The GFI and AGFI range between 0 and 1, with a value of over 0.9 generally indicating acceptable model fit. In general, values more than 0.90 for GFI are generally accepted as indications of very good overall model fit (GFI > 0.90).

RESULTS

An initial comparison of average speeds between the two experiments revealed notable differences. Specifically, in the naturalistic driving experiment, the average speed was 47.5 km/h, whereas in the simulator experiment, the average speed was higher at 58.9 km/h. This variation may be attributed to the controlled and safe environment of the simulator, which potentially encourages participants to drive at higher speeds compared to real-world road conditions, where adherence to traffic regulations and safety concerns play a greater role. The distribution of average speeds across both experimental designs is illustrated in **Figure 3**.

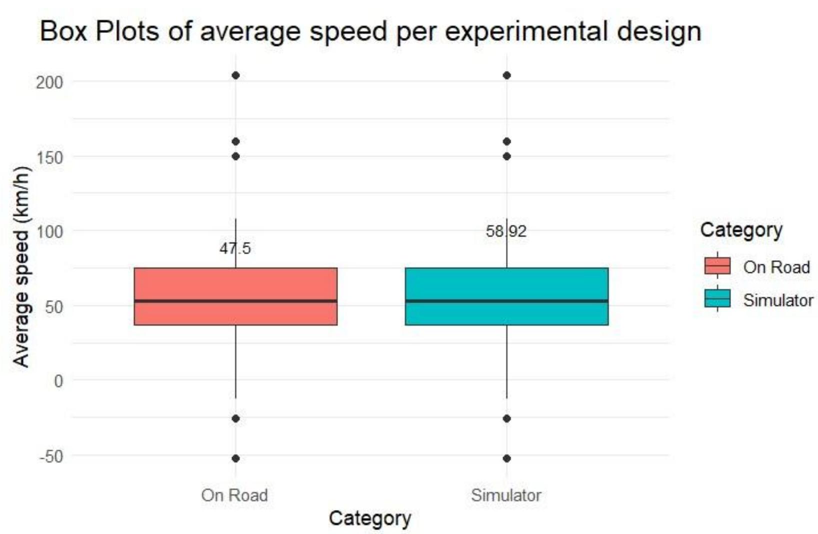

Figure 3 Box plots of average speed per driving experiment

Driving Simulator Analyses

GLM Results

Several regression models were tested using different combinations of variables. For each configuration, multiple alternatives were evaluated by comparing their respective log-likelihood values. GLM investigated the relationship between the headway and several explanatory variables of task complexity and coping capacity. More specifically, the dependent variable of the developed model was the dummy variable "headway", which was coded with 1 if there was a headway event and with 0 if not.

For task complexity, the variable used was time indicator. Concerning coping capacity - driver state, the variables used were duration, average speed, time-to-collision (TTC), fatigue and hand-on event. The "hands-on event" variable, indicating when a driver places their hands on the wheel, can be used to infer instances of driver distraction. If a driver frequently needs to put their hands back on the wheel, it might suggest they were previously distracted or not fully engaged in manual driving tasks. It should be clarified that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox are not available in the simulator experiment (as only a single vehicle configuration was used) while socio-demographic characteristics, such as gender or age were not statistically significant at a 95% confidence level; thus, these variables were not included in the models. The model parameter estimates are summarized in **Table 1**.

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

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	0.859	0.221	3.896	< .001	-
Time indicator	-0.690	0.318	-7.443	< .001	1.209
Average speed	0.742	0.080	9.231	< .001	1.020
Time to collision	0.004	3.116	14.300	< .001	1.018
Duration	-5.658	1.395	-4.057	< .001	1.040
Fatigue	5.088	1.587	3.206	0.001	1.114
Hands on wheel	5.369	2.311	2.323	0.020	1.076
Summary statistics					
AIC	4546.08				
BIC	4141.62				
Degrees of freedom	33820				

Findings derived from **Table 1** demonstrated that all the explanatory variables were statistically significant at a 95% confidence level. In addition, there was no issue of multicollinearity as the VIF values are much lower than 5. Regarding the coefficients, it was found that time of the day was negatively correlated with headway, which means that drivers tend to keep safer distances from the vehicle in front of them during the night. This may probably be due to the fact that there is no heavy traffic during night hours; thus, headway events are avoided.

Moreover, it was found that indicators of coping capacity, such as average speed and TTC had a positive impact on headway. This means that higher average speeds are associated with an increased likelihood of headway events. Additionally, fatigue and hands-on events were positively correlated with headway. This means that both driver's fatigue and the occurrence of hands-on events are associated with more frequent instances of reduced following distances (closing headway). Fatigue can impair a driver's ability to maintain consistent headway, resulting in more frequent adjustments and closing gaps. Similarly, hands-on events, where drivers re-engage with the steering wheel, often occur in response to challenging driving conditions, leading to more frequent and closer following distances as drivers navigate these situations.

On the other hand, duration found to be negatively correlated with headway events. This indicates that as the duration of a trip increases, the likelihood of headway events decreases. Longer trips might involve more consistent driving patterns and steadier speeds, leading to fewer instances where drivers need to adjust their following distance. Additionally, drivers may become more relaxed and maintain a more constant headway over extended periods, reducing the frequency of headway adjustments.

SEM Results

Following the exploratory analysis, the variables related to the latent variables "task complexity" and "coping capacity" were estimated from various indicators. Risk was measured by means of the STZ levels for headway (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').

The latent variable of task complexity was measured by means of the exposure indicators of trip duration and distance travelled. It was found that distance and duration had a positive correlation with task complexity. In addition, the latent coping capacity was measured by means of driver state indicators, such as TTC, average speed, hands-on event and fatigue. It was revealed that hands-on event and fatigue were positively correlated with coping capacity, indicating that fatigued drivers tend to be more cautious in their driving. When drivers experience fatigue, they often become more aware of their limitations and the potential dangers of their condition. As a result, they may adopt more cautious driving behaviours, such as reducing speed, increasing following distance and avoiding risky manoeuvres, in an effort to compensate for their reduced alertness and reaction times.

On the other hand, TTC and average speed were negatively correlated with coping capacity. This means that as TTC and average speed increase, an individual's coping capacity tends to decrease. In other words, higher TTC and faster driving speeds are associated with lower ability to manage stress and challenges. This negative correlation suggests that when drivers experience longer TTC and higher speeds, they may find it more difficult to cope with the demands and stressors of driving. Conversely, lower TTC and slower speeds might be linked to higher coping capacities, indicating that these drivers are better equipped to handle stress and challenges.

The SEM between the latent variables revealed some interesting findings: first, task complexity and coping capacity were inter-related with a positive correlation (regression coefficient=0.14). This positive correlation indicated that higher task complexity was 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 showed a positive coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=0.53). On the other hand, the structural model between coping capacity and risk showed a negative coefficient, which means that increased coping capacity relates to decreased risk according to the model (regression coefficient=-4.29). The respective path diagram of the SEM is presented in **Figure 4**.

To evaluate the model fit of the SEM, several goodness-of-fit indices were computed. The GFI and AGFI were used to assess the extent to which the hypothesized model reproduces the observed covariance structure. The resulting GFI was 0.973 and AGFI was 0.952, both exceeding the conventional threshold of 0.90, indicating a very good model fit. Additional indices, including the CFI = 0.966, TLI = 0.944 and RMSEA = 0.079, further support the adequacy of the model and confirm the robustness of the latent structure. **Table 3** summarizes the model fit of SEM applied for headway, while residual variances details for both driving experiments are presented in **Table 4**.

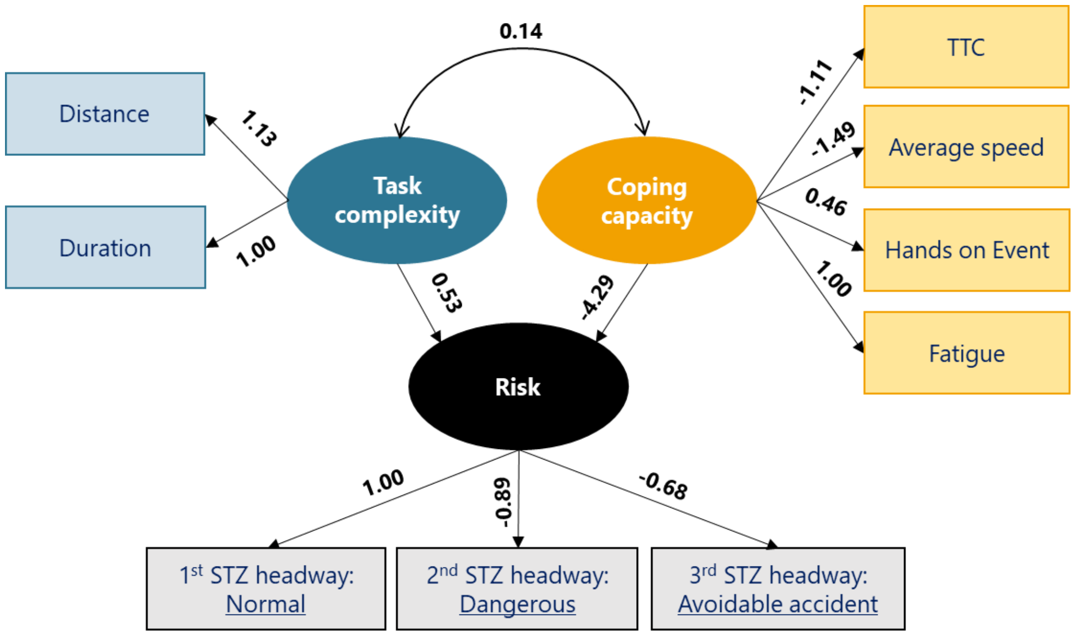

Figure 4 SEM results of task complexity and coping capacity on risk (STZ headway) - simulator experiment

Naturalistic Driving Analyses

GLM Results

Similar to the simulator analyses, GLM investigated the relationship between the headway and several explanatory variables of task complexity and coping capacity. More specifically, the dependent variable of the developed model is the dummy variable "headway", which is coded with 1 if there is a headway event and with 0 if not. For task complexity, the variables used are time indicator and weather. Concerning coping capacity - vehicle state, the variables used are fuel type, vehicle age and gearbox, while for coping capacity - driver state, the variables used are duration, harsh accelerations, harsh brakings, average speed, gender and age. The model parameter estimates are summarized in **Table 2**.

Findings derived from **Table 2** demonstrated that all the explanatory variables were statistically significant at a 95% confidence level. In addition, there was no issue of multicollinearity as the VIF values are much lower than 10. With respect to the coefficients, it was found that time of the day was negatively correlated with headway, which means that drivers tend to keep safer distances from the vehicle in front of them during the night. This may probably be due to the fact that there is no heavy traffic during night hours; thus, headway events are avoided. The weather variable showed a negative correlation with headway, indicating that fewer headway events occur during adverse weather conditions, such as rain. This suggests that drivers tend to exercise more caution and maintain longer following distances when windshield wipers are active, reflecting an increased emphasis on safety in adverse weather conditions.

Furthermore, vehicle age appeared to have a positive relationship with the dependent variable, (i.e. headway), indicating that as the vehicle age increases, the likelihood of headway events also increases. This suggests that older vehicles are more frequently involved in headway events, which could be due to various factors, such as the cautious driving habits of owners of older vehicles or the reduced performance and response times of older vehicles necessitating greater following distances. Interestingly, fuel type and gearbox were negatively correlated with headway. In particular, the negative value of the "fuel type" coefficient implied that when the fuel type was diesel, the headway percentage became lower. This suggests that vehicles running on diesel are associated with a lower frequency of headway events compared to those running on hybrid electric or petrol. Similarly, the negative value of the "gearbox" coefficient demonstrated that vehicles with an automatic gearbox experienced fewer headway events. This indicates that vehicles with automatic transmissions are less likely to encounter headway events compared to those with manual transmissions, possibly due to the smoother and more consistent driving patterns facilitated by automatic gearboxes.

TABLE 2 Parameter estimates and multicollinearity diagnostics of the GLM for headway

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	-0.339	0.003	-14.275	< .001	-
Time indicator	-4.713	1.527	-3.086	0.002	1.001
Weather	-0.059	0.007	-2.852	< .001	1.003
Fuel type - Diesel	-3.432	1.906	-8.094	< .001	3.888
Vehicle age	3.194	1.601	9.942	< .001	4.765
Gearbox - Automatic	-5.122	1.213	-4.032	0.003	2.851
Duration	8.283	3.969	19.871	< .001	1.279
Harsh brakings	5.707	2.456	32.562	< .001	3.396
Harsh accelerations	4.590	2.201	25.239	< .001	3.404
Average speed	7.686	5.019	36.273	< .001	1.103
Gender - Female	-2.097	1.349	-2.775	< .001	1.495
Age	3.764	1.879	3.203	< .001	6.119
Summary statistics					
AIC	568996.72				
BIC	339955.85				
Degrees of freedom	822,164				

Moreover, it was revealed that indicators of coping capacity – driver state, such as duration, harsh accelerations, harsh brakings and average speed had a positive impact on headway. This means that longer trip duration, instances of harsh accelerations and brakings and higher average speeds are associated with an increased likelihood of headway events. These factors suggest that more aggressive driving behaviours and longer driving times contribute to more frequent occurrences of maintaining following distances.

Taking into account socio-demographic characteristics, gender was negatively correlated with headway. 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 headway percentage was lower. This suggests that female drivers perform fewer headway events and tend to be more cautious in maintaining following distances compared to male drivers. On the other hand, age was positively correlated with headway, indicating that as the driver's age increases, the likelihood of headway events also increases. This suggests that older drivers tend to have more headway events, which could be due to various factors, such as slower reaction times, leading to a greater need to maintain safe following distances.

SEM Results

The latent variable of task complexity was measured by means of the environmental indicator of time of the day and weather. Exposure indicators, such as trip duration was also included in the task complexity analysis. It was revealed that time of the day, weather and duration had a positive correlation with task complexity. In addition, the latent coping capacity is measured by means of both vehicle and driver state indicators. Vehicle state includes variables such as vehicle age and fuel type, while driver state includes indicators, such as average speed, gender and age. Results indicated that vehicle age, fuel type, gender and driver’s age were positively correlated with coping capacity. These factors imply that certain vehicle characteristics and driver demographics contribute to enhanced coping mechanisms in various driving conditions. Interestingly, average speed appeared to have a negative impact on coping capacity. This suggests that as the average speed increases, the ability of drivers to manage and respond to driving demands and challenges effectively decreases. Higher speeds likely reduce the time available for decision-making and increase the complexity of driving tasks, thereby diminishing coping capacity.

The structural model between the latent variables showed some interesting findings: first, task complexity and coping capacity are inter-related with a positive correlation (regression coefficient=0.10). This positive correlation indicated that higher task complexity was 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 revealed a positive coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=13.19). On the other hand, the structural model between coping capacity and risk showed a negative coefficient, which means that increased coping capacity relates to decreased risk according to the model (regression coefficient=-0.05). The respective path diagram of the SEM for headway is presented in **Figure 5**.

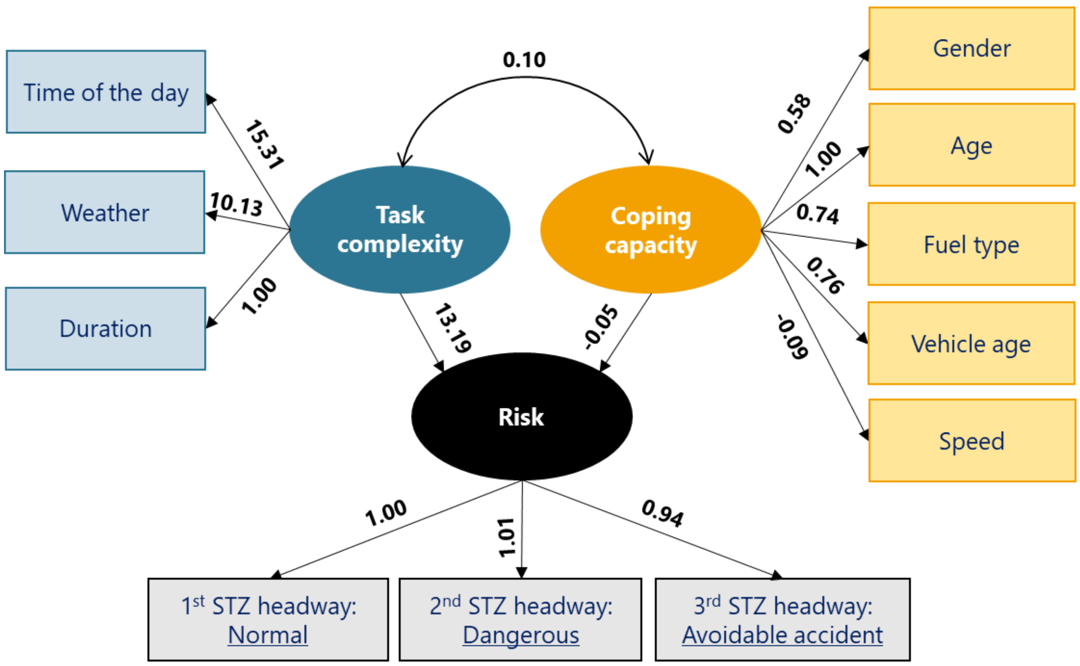

Figure 5 SEM results of task complexity and coping capacity on risk (STZ headway) - naturalistic driving experiment

The CFI of the model is equal 0.945; TLI is 0.927 and RMSEA is 0.106. **Table 3** summarizes the model fit of SEM applied for headway per driving experiment. The resulting GFI was 0.921 and AGFI was 0.914, both exceeding the conventional threshold of 0.90, indicating a very good model fit. These indices confirmed that the proposed latent structure, relating task complexity, coping capacity and risk (headway), adequately represented the observed data relationships in both driving experiments.

TABLE 3 Model Fit Summary for STZ headway per driving experiment

Model Fit measures	Values	
	Simulator Experiment	Naturalistic Experiment
CFI	0.966	0.945
TLI	0.944	0.927
RMSEA	0.079	0.106
GFI	0.973	0.921
AGFI	0.952	0.914
Hoelter's critical N (α = .05)	247.93	224.06
Hoelter's critical N (α = .01)	300.04	241.36
AIC	65281.04	2.043×10+7
BIC	65445.96	2.043×10+7

Residual variances details for headway per driving experiment are presented in **Table 4**.

TABLE 4 Residual variances STZ headway per driving experiment

Variable	Estimate	Std. Error	z-value	P(>|z|)
Simulator experiment				
Distance	0.108	0.024	4.576	< .001
Duration	0.107	0.023	4.542	< .001
Fatigue	0.950	0.024	39.002	< .001
TTC	0.939	0.025	38.280	< .001
Average speed	0.890	0.026	33.990	< .001
HandsOnEvent	0.989	0.024	40.565	< .001
Headway_STZ_level_0	-0.242	0.059	-4.082	< .001
Headway_STZ_level_1	0.177	0.049	3.652	< .001
Headway_STZ_level_2	0.422	0.029	14.344	< .001
Naturalistic experiment				
Duration	0.996	0.001	67.537	< .001
Time indicator	0.564	8.911×10-4	63.976	< .001
Weather	0.006	6.643×10-4	8.283	< .001
Age	0.035	6.662×10-4	51.797	< .001
Average speed	0.991	0.001	66.324	< .001
Fuel type	0.473	8.009×10-4	59.334	< .001
Vehicle age	0.436	7.641×10-4	57.346	< .001
Gender	0.677	0.001	64.155	< .001
Headway_STZ_level_0	0.055	1.368×10-4	40.312	< .001
Headway_STZ_level_1	0.032	1.188×10-4	26.257	< .001
Headway_STZ_level_2	0.138	2.400×10-4	57.352	< .001

DISCUSSION

The performance and insights from the naturalistic experiment compared with those from the simulator experiment revealed key interesting findings. To begin with, when comparing average speeds between naturalistic and simulator experiments, a significant difference was observed. Specifically, the average speed in on-road trials was lower compared to the simulator experiments. Real-world driving involves navigating traffic, dealing with road hazards and adhering to strictly enforced speed limits, all of which necessitate frequent speed adjustments and lower overall speeds. Moreover, the potential for road crashes and the unpredictability of other drivers in actual driving conditions often result in higher levels of caution and stress, leading drivers to adopt more conservative driving behaviour. In contrast, simulator experiments provide a controlled environment, allowing for higher speeds.

Regression analysis was conducted to examine the interaction of road, vehicle and driver variables on crash risk. The GLMs revealed consistent patterns across both simulator and naturalistic experiments, indicating that despite differing conditions, the core relationships among variables, particularly task complexity and coping capacity, remained stable. A negative correlation between time of day and headway was found in both environments, showing that drivers tend to maintain safer following distances during nighttime. This may be due to reduced traffic volumes and increased caution during these hours.

The analysis also showed that diesel vehicles had shorter headways compared to other fuel types, potentially due to their greater torque and acceleration capability. Automatic gearboxes were associated with fewer headway events, possibly reflecting smoother acceleration and more relaxed driving behavior. This aligns with Török's *(14)* findings that automation can reduce crash severity compared to manual control. Furthermore, it was demonstrated that the majority of the indicators of coping capacity had a positive relationship with headway. For instance, speed had a positive effect on headway both on the naturaistic and the simulator experiment. Higher speeds, TTC, fatigue and hands-on events were linked to increased following distances, reflecting cautious adaptation under challenging conditions. Interestingly, while increased speed led to longer headways in this study, this contrasts with Brackstone et al. *(15)*, who found the opposite trend. Lastly, socio-demographic factors also played a role; female drivers tended to maintain larger headways, while older drivers were associated with more frequent headway events.

Through the application of SEM models, latent analysis from the simulator and naturalistic driving experiments revealed complicated effects of task complexity and coping capacity on risk. In particular, both simulator and on-road results revealed a positive correlation between task complexity and crash risk, influenced by factors such as time of day and adverse weather, which amplify the difficulty of driving tasks and contribute to reduced attention and slower reaction times. Drivers experienced increased cognitive workload when dealing with in-vehicle systems or navigating complex environments, further heightening the risk of a crash.

Meanwhile, coping capacity demonstrated a negative correlation with crash risk in both experimental contexts, meaning that higher coping capacity is associated with a lower likelihood of crashes. This can be attributed to the fact that drivers with greater coping abilities are more capable of managing demanding driving situations. They are generally better at handling stress, making quick and accurate decisions and maintaining effective vehicle control, all of which support safer driving. On the other hand, drivers with lower coping capacity may find it difficult to manage complex scenarios, resulting in a heightened risk of crashes.

The latent analysis also demonstrated a positive relationship between task complexity and coping capacity, suggesting that drivers' ability to cope tended to increase as driving tasks became more demanding. When faced with challenging conditions, such as driving in adverse weather, drivers appeared to engage more actively with the driving task, effectively regulating their responses to potential hazards. This increased focus encouraged the development of advanced driving strategies and skills, enabling them to navigate difficult situations more efficiently. As a result, exposure to complex driving scenarios contributed to enhanced driving competence and a stronger ability to respond to unforeseen challenges on the road. It was also found that task complexity had a stronger influence on risk than coping capacity. In addition, a positive correlation between risk and the STZ indicators was observed, with the highest values appearing in the normal driving phase (STZ level 1).

A primary limitation of this study is the simulator experimental sample size of drivers which may impact the generalizability of the findings. Secondly, the dataset, drawn from the naturalistic experiment may not fully capture the diversity of driving behaviour across various regions, populations or transport modes and may pose limitations on the generalisability of conclusions on a global scale. The impact of participants' health or medical status was not taken into account.

Future research efforts could consider additional and drivers' age groups, while larger datasets from across the world could enhance the analysis procedure. Demographic characteristics such as educational level or driving experience could be also taken into consideration. The sample size could be strengthened, while comparisons among different countries or transport modes could be also made. Moreover, additional task complexity and coping capacity risk indicators (i.e. driving profiles) could be utilized, while other methodologies, such as deep learning techniques could be also implemented.

CONCLUSIONS

The aim of this study was to improve the Driver Safety Tolerance Zone (STZ) through a holistic analysis of road, vehicle and behavioural risk factors. A comparative approach based on driving simulator and naturalistic data was implemented and the complex interrelations among task complexity, coping capacity and crash risk were identified.

GLMs were conducted to examine the the key correlations among observed metrics and identify the effect of task complexity and coping capacity on specific driving performance parameters. Moreover, SEMs were performed to identify the impact between latent and observable variables of task complexity and coping capacity with crash risk.

The findings revealed that task complexity was positively associated with crash risk, particularly under challenging conditions, such as night-time driving and adverse weather. In contrast, coping capacity was shown to be negatively correlated with crash risk, indicating that drivers with better physiological, behavioural or vehicle-related coping characteristics were more likely to operate safely under demanding conditions. Interestingly, a positive relationship was also found between task complexity and coping capacity, meaning that drivers become more engaged and adaptive when confronted with difficult driving situations.

This study presents a holistic approach to road safety by conceptualizing the environment, vehicle and driver as interconnected components of a unified system. Taking into account both naturalistic and simulator data and applying the STZ concept, the research captured the dynamic interplay between task complexity, coping capacity and crash risk. The findings demonstrated that these variables are not only individually impactful but also positively interrelated, suggesting that drivers tend to compensate for complex driving conditions through increased engagement. This integrated perspective enhances the accuracy of risk assessment and supports the development of more effective, targeted safety interventions. Overall, the STZ models proved to be a robust tool to understand driver behaviour under varying conditions and provided a valuable foundation for data-driven safety planning, Intelligent Transport System design and informed policy-making.

ACKNOWLEDGMENTS
The research was funded by the EU H2020 i-DREAMS project (Project Number: 814761) funded by European Commission under the MG-2-1-2018 Research and Innovation Action (RIA).

AUTHOR CONTRIBUTIONS
The authors confirm contribution to the paper as follows: study conception and design: Eva Michelaraki, George Yannis; data collection: Eva Michelaraki; analysis and interpretation of results: Eva Michelaraki, George Yannis; draft manuscript preparation: Eva Michelaraki. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF CONFLICTING INTERESTS
The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

FUNDING
The authors disclosed no financial support for the research, authorship, and/or publication of this article.

REFERENCES

1. Fu, C., Lu, Z., Ding, N., & Bai, W. (2024). Distance headway-based safety evaluation of emerging mixed traffic flow under snowy weather. Physica A: Statistical Mechanics and its Applications, 642, 129792.

2. Risto, M., & Martens, M. H. (2013). Time and space: The difference between following time headway and distance headway instructions. Transportation research part F: traffic psychology and behaviour, 17, 45-51.

3. Luo, S., Yi, X., Shao, Y., & Xu, J. (2022). Effects of distracting behaviors on driving workload and driving performance in a city scenario. International journal of environmental research and public health, 19(22), 15191.

4. Parkes, A. M., Luke, T., Burns, P. C., & Lansdown, T. (2007). Conversations in cars: the relative hazards of mobile phones (Vol. 664). Transport and Road Research Laboratory.

5. Engström, J., Johansson, E., & Östlund, J. (2005). Effects of visual and cognitive load in real and simulated motorway driving. Transportation research part F: traffic psychology and behaviour, 8(2), 97-120.

6. Michelaraki, E., Katrakazas, C., Brijs, T., & Yannis, G. (2021). Modelling the safety tolerance zone: Recommendations from the i-DREAMS project. In 10th International congress on transportation research.

7. Hastie, T. J., & Pregibon, D. (2017). Generalized linear models. In Statistical models in S (pp. 195-247). Routledge.

8. Dunn, P. K., & Smyth, G. K. (2018). Chapter 10: Models for Counts: Poisson and Negative Binomial GLMs. In Generalized Linear Models With Examples in R (pp. 371-424). New York, NY: Springer New York.

9. Collins, M., Dasgupta, S., & Schapire, R. E. (2001). A generalization of principal components analysis to the exponential family. Advances in neural information processing systems, 14.

10. Harrison, L., & Friston, K. J. (2007). Effective connectivity. Statistical parametric mapping: the analysis of functional brain images, 508-521.

11. Stein, C. M., Morris, N. J., & Nock, N. L. (2011). Structural equation modeling. In Statistical human genetics: Methods and protocols (pp. 495-512). Totowa, NJ: Humana Press.

12. Washington, S., Karlaftis, M., Mannering, F., & Anastasopoulos, P. (2020). Statistical and econometric methods for transportation data analysis. Chapman and Hall/CRC.

13. Vrieze, S. I. (2012). Model selection and psychological theory: a discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Psychological methods, 17(2), 228.

14. Török, Á. (2020). A novel approach in evaluating the impact of vehicle age on road safety. Promet-Traffic & Transportation, 32(6), 789-796.

15. Brackstone, M., Waterson, B., & McDonald, M. (2009). Determinants of following headway in congested traffic. Transportation Research Part F: Traffic Psychology and Behaviour, 12(2), 131-142.