Modelling the inter-relationship among task complexity, coping capacity and crash risk

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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. Taking to account the framework of the i-DREAMS project, this paper endeavors to model the inter-relationship among task complexity, coping capacity (i.e. vehicle and operator state) and crash risk. A complete Structural Equation Model (SEM) was developed for each country of analysis (i.e., Belgium, United Kingdom, Germany) to describe the interactions between task complexity and coping capacity (i.e., related to both vehicle state and operator state factors). 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.

Keywords: *i-DREAMS Project; Task Complexity; Coping Capacity; Crash Risk; Structural Equation Models.*

Περίληψη

Λαμβάνοντας υπόψη τη σημαντική επιρροή του ανθρώπινου παράγοντα στην ασφαλή οδηγική συμπεριφορά, το έργο i-DREAMS ανέπτυξε μια "Ζώνη Ανοχής Ασφάλειας (STZ)" για να καθορίσει το ακριβές όριο όπου ο αυτορρυθμιζόμενος έλεγχος μπορεί να διατηρηθεί με ασφάλεια. Λαμβάνοντας υπόψη το πλαίσιο του έργου i-DREAMS, η παρούσα έρευνα αποσκοπεί στην μοντελοποίηση της αλληλεπίδρασης μεταξύ της δυσκολίας του έργου της οδήγησης, της ικανότητας αντιμετώπισης (δηλ. της κατάστασης του οχήματος και του χειριστή) και του κινδύνου σύγκρουσης. Για κάθε χώρα ανάλυσης (δηλ. Βέλγιο, Ηνωμένο Βασίλειο, Γερμανία, Ελλάδα) αναπτύχθηκε ένα πλήρες Μοντέλο Δομικών Εξισώσεων (SEM) για την περιγραφή των αλληλεπιδράσεων μεταξύ της δυσκολίας του έργου της οδήγησης και της ικανότητας αντιμετώπισης (δηλ. που σχετίζονται τόσο με την κατάσταση του οχήματος όσο και με τους παράγοντες της κατάστασης του χειριστή). Τα αποτελέσματα έδειξαν θετική συσχέτιση της πολυπλοκότητας του έργου της οδήγησης και της ικανότητας αντιμετώπισης του κινδύνου που σημαίνει ότι η ικανότητα αντιμετώπισης του οδηγού αυξάνεται όσο αυξάνεται η δυσκολία στο έργο της οδήγησης.

Λέξεις κλειδιά: *έργο i-DREAMS; δυσκολία του έργου της οδήγησης; ικανότητα αντιμετώπισης; κίνδυνος ατυχήματος; Δομικά Μοντέλα Εξισώσεων.*

1. Introduction

Road safety is of utmost importance in order to reduce crash risk, prevent injuries, and save lives. Every year, numerous lives are lost and countless individuals sustain severe injuries as a result of road crashes. Several factors have a significant impact on road safety. These factors can contribute to the occurrence of road crashes and influence the severity of injuries sustained. For instance, human behavior plays a critical role in road safety. Factors such as speeding, distracted driving (e.g., mobile phone use), impaired driving (due to alcohol, drugs, or fatigue), aggressive driving, and non-compliance with traffic regulations can increase the crash risk. In addition, the design, condition, and maintenance of roads and infrastructure can impact road safety. Poorly designed roads, inadequate signage, absence of pedestrian crossings, lack of proper lighting, and insufficient maintenance can contribute to crashes and injuries.

At the same time, the condition and safety features of vehicles also have a strong impact on road safety. Indicators such as vehicle maintenance, tire condition, brake functionality, and the presence of safety technologies (e.g., airbags, anti-lock braking systems) can significantly affect crash outcomes. Similarly, environmental conditions can affect road safety. Factors such as adverse weather conditions (e.g., rain, snow, fog), poor visibility, and uneven road surfaces can increase the likelihood of crashes. Moreover, socioeconomic factors, such as income level, education, and access to transportation resources, can indirectly influence road safety. Disparities in these factors may contribute to differences in driver behaviors, vehicle conditions, and road infrastructure quality.

Based on the above, the overall objective of the i-DREAMS project is to setup a framework for the definition, development, testing and validation of a context-aware safety envelope for driving (‘Safety Tolerance Zone’), within a smart Driver, Vehicle & Environment Assessment and Monitoring System (i-DREAMS). Taking into account driver background factors and real-time risk indicators associated with the driving performance as well as the driver state and driving task complexity indicators, a continuous real-time assessment will be made to monitor and determine if a driver is within acceptable boundaries of safe operation (i.e. Safety Tolerance Zone). Moreover, the to-be-developed i-DREAMS platform will offer a series of in-vehicle interventions, meant to prevent drivers from getting too close to the boundaries of unsafe operation and to bring them back into the Safety Tolerance Zone (STZ) while driving. The safety-oriented interventions will be developed to inform or warn the driver real-time in an effective way as well as on an aggregated level after driving through an app- and web-based gamified coaching platform, thus reinforcing the learning of safer driving habits/behaviors. Consequently, the i-DREAMS platform will allow the implementation of the two aforementioned safety interventions, meant to motivate and enable human operators to develop the appropriate safety-oriented attitude.

In-vehicle interventions are intended to aid and support vehicle operators in real-time (i.e., while driving). Depending on how urgent the collision hazards are, a ‘normal driving' phase, a 'danger' phase, and a 'avoidable accident' phase can be distinguished. During the ‘normal’ phase, the monitoring platform of the i-DREAMS detects no irregularities in a vehicle operator’s driving style and thus no immediate intervention is necessary. The i-DREAMS monitoring module detects abnormalities from the vehicles operator’s driving style during the ‘danger’ phase, and the potential of a crash is present. In that instance a warning signal will be provided in order to guide the driver within acceptable safety boundaries of operation. Finally, concerning the ‘avoidable accident’ phase the likelihood of a collision occurring becomes imminent if the vehicle operator fails to adjust to the current conditions promptly and appropriately. To aid the vehicle operators in preventing a crash, a more prominent warning signal is introduced.

Post-trip interventions are not operational while driving, but they are dependent on what happens throughout the journey. They are based on all of the raw data collected by the i-DREAMS sensors, which is then processed and fused to provide information on a vehicle operator's driving style, how it evolved during a trip, how many (safety-critical) incidents occurred, and under what conditions these incidents occurred. This data may then be turned into feedback for vehicle operators via an app in a pre- or post-trip context. To develop a longer-term connection with individual vehicle operators, app-supported feedback can be supplemented with the usage of a web-based coaching platform that includes gamification aspects to motivate drivers to concentrate on gradual and consistent progress.

According to the level of unsafe driving behavior, the STZ is categorized into three levels: ‘Normal’, ‘Dangerous’ and ‘Avoidable Accident’. First off, the ‘Normal’ level denotes a situation with a minimal crash risk and thus safe driving practices. Second, the 'Dangerous' level refers to the chance of a crash increasing, but the crash is not unavoidable. Finally, the ‘Avoidable Accident’ level denotes a high risk of a potential crash occurring, but there is still enough time for drivers to act and avoid the incident.

Following the i-DREAMS project’s goal, this study aims to investigate the interaction between task complexity and coping capacity (i.e., related to both vehicle state and operator state factors). To achieve this goal a complete Structural Equation Model (SEM) developed and a set of quantitative effects of indicators was created, describing the impacts of vehicle, operator and context characteristics on risk under different conditions. Apart from SEMs, Generalized Linear Models (GLMs) were also used and the goodness-of-fit-metrics for the models were explained.

The paper is structured as follows. At the beginning, a detailed overview of the project and its overall objective is provided. Following that, a comprehensive literature review on the statistical analysis of driving behavior is presented. Furthermore, the data collection process is thoroughly described. The research approach is then outlined, including the theoretical foundations of the models used. Finally, the results are provided, followed by substantial conclusions about the relationship between crucial factors such as task complexity and coping capacity on risk.

2. Background

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 assessment of task difficulty and coping ability forms the basis of the i-DREAMS platform.

2.1 Definitions

Task complexity plays a significant role in influencing crash risk on the roads. The complexity of driving tasks refers to the level of cognitive demand and physical effort required to perform them. Factors contributing to task complexity include traffic density, road infrastructure, weather conditions, presence of distractions, and time pressure, among others. The current state of the real-world environment in which a vehicle is being driven is related to task complexity. Since the difficulty of the job placed on the vehicle operator depends on a number of distinct individual factors, a multi-dimensional approach is taken to further operationalize this idea. The registration of road layout (i.e., highway, rural, urban), time and place, traffic volumes (i.e., high, medium, low), and weather is particularly used to assess job complexity context.

On the other hand, coping capacity refers to an individual driver's ability to effectively manage and adapt to complex driving tasks. It encompasses factors such as experience, skills, perceptual abilities, decision-making processes, and the availability of appropriate coping strategies. Drivers with high coping capacity can better handle complex tasks, maintain situational awareness, and make appropriate decisions to mitigate crash risk. More precisely, estimates of the latent variables related to "vehicle state" are made using a variety of criteria. The word "vehicle" refers to three different things, as follows:

- Technical specifications, measured based on average speed, braking power, acceleration performance, etc.
- Actuators & admitted actions, as determined by the steering wheel, accelerator, brakes etc.
- Current status, measured on the basis of fuel efficiency, schedule maintenance), real-time information either from on board systems (OBD II, FMS, Tachometer), Telematics/GPS, or smartphone, or additional information coming from Advanced Driver Assistance Systems (ADAS) systems - (headway & collision monitoring, pedestrian warning, lane keeping monitoring, on board cameras, etc.

The latent variables related to "operator state" are also estimated using a variety of measures. The factor "operator" has six components, as follows:

- Mental state, measured based on metrics on alertness, attention, emotions, etc.
- Behavior, measured on the basis of metrics such as speeding, harsh acceleration / braking / cornering, seat belt use etc.
- Competencies, measured based on metrics on risk assessment, attention regulation, self-appraisal, etc.
- Personality, measured based on metrics on adventure seeking, disinhibition, experience seeking, boredom susceptibility, etc.
- Sociodemographic profile, measured based on age, gender, experience, socio-economic status, nationality, ethnicity, cultural identity, etc.
- Health status, measured based on metrics on current symptoms, neurologic and cardiovascular indicators, medication, etc.

The conceptual foundation of the i-DREAMS platform for the prediction of risk as a function of coping capacity and task complexity is shown in Figure 1.

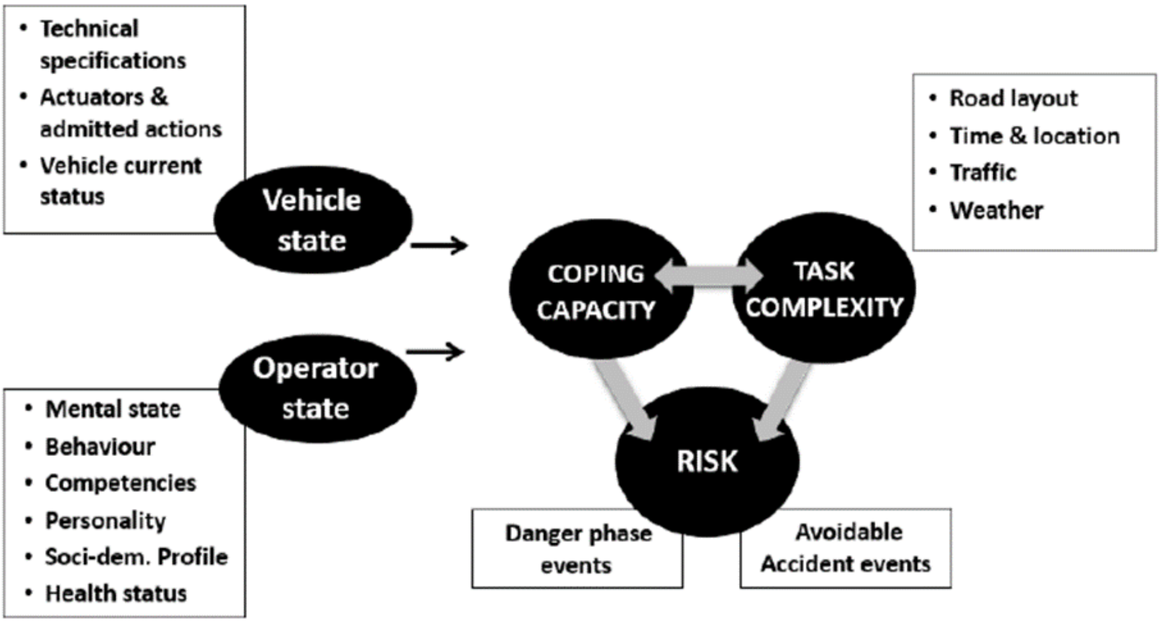

Figure 1: *Post-hoc prediction of risk in function of coping capacity and task complexity*

2.2 Road safety aspects

Road safety is a pressing global concern, with millions of lives lost or impacted by traffic crashes each year. To effectively address this issue, researchers and policymakers have turned to advanced statistical modeling techniques, such as Structural Equation Models (SEMs), to gain a deeper understanding of the complex relationships between various factors contributing to road crashes.

SEMs have emerged as a powerful tool for analyzing the intricate interplay between observed variables and latent constructs in road safety research. They allow researchers to explore the direct and indirect effects of multiple factors on road safety while providing a methodology for direct modelling of latent variable, separating measurement errors from true scores of attributes (Yuan & Bentler, 2006). This makes SEMs particularly suitable for studying the multifaceted nature of road safety, where numerous factors interact to influence the occurrence and severity of crashes.

The application of SEMs in recent road safety research has yielded valuable insights into the underlying factors contributing to crashes and their consequences. By modeling and examining the relationships between various risk factors, SEMs help researchers identify key predictors of road crashes, understand their interrelationships, and develop effective intervention strategies (Shah et al., 2018).

One area where SEMs have been applied in road safety is the modeling of driver behavior and its impact on crash occurrence. By incorporating multiple variables, such as driver characteristics, environmental factors, and vehicle conditions, SEMs provide insights into their combined influence on driving behavior and crash severity (J.-Y. Lee et al., 2008; Scott-Parker et al., 2013; Zhao et al., 2019). These models allow researchers to uncover the underlying mechanisms through which these factors interact and contribute to road safety.

In conclusion, the use of SEMs has proven invaluable in advancing road safety research. These models provide a comprehensive framework for understanding the intricate relationships and interdependencies among various factors contributing to road crashes. By elucidating causal mechanisms and mediating/moderating effects, SEMs enable researchers to develop targeted interventions, evaluate policy effectiveness, and ultimately enhance road safety outcomes.

3. Data Description

3.1 Experimental processing

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) of all event variables, such as speeding, headway, overtaking and fatigue (level 1 'normal driving' used as the reference case). Data from Belgian, German and UK car drivers were analyzed. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 120 car drivers, 5,643 trips (104,195 minutes)
- Phase 2: real-time interventions - 125 car drivers, 6,188 trips (109,341 minutes)
- Phase 3: real-time & post-trip interventions - 130 car drivers, 6,519 trips (117,381 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 130 car drivers, 8,558 trips (169,695 minutes)

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. As the first stage of the field trials, pilot testing was performed for a limited number of vehicles (i.e., five vehicles) for each test site. The purpose of the pilot tests was to fine-tune the i-DREAMS technology. This includes all the processes associated with production, installation and interventions but also collection, processing and visualization of data. In addition, it offered the chance to implement changes based on user feedback before transitioning to large-scale testing.

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 & gamification) on driving behavior. Figure 2 provides an overview of the different phases of the experimental design of the i-DREAMS on-road study.

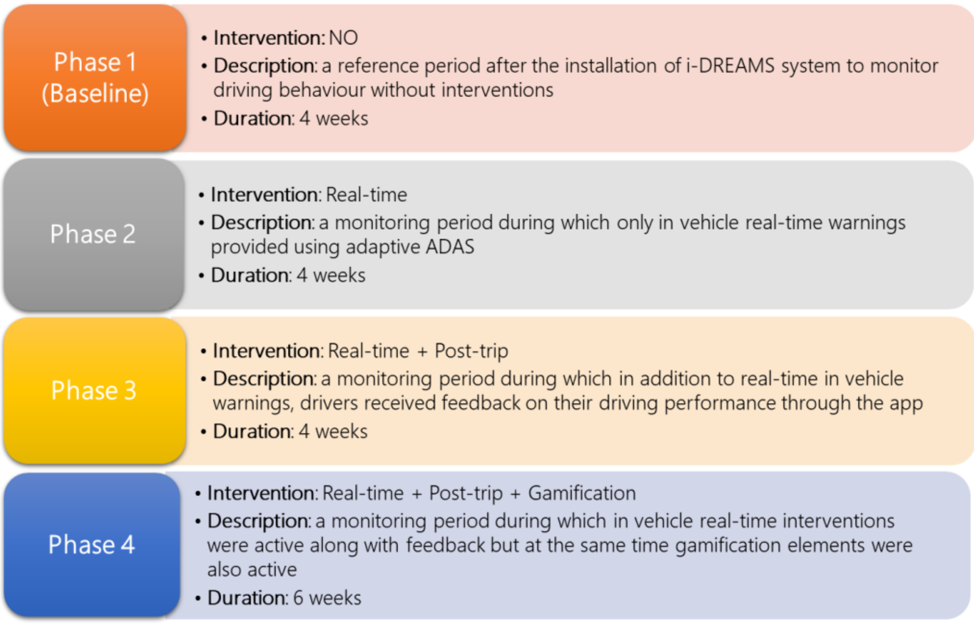

Figure 2: *Overview of the different phases of the experimental design of the i-DREAMS on-road study*

3.2 Variables used to define task complexity and coping capacity

The most appropriate variables which were used in order to define task complexity and coping capacity (vehicle and operator state) along with the variables that were finally utilized to represent risk are shown in Table 1.

With regards to car wipers, considered as an indicator of weather conditions, can be used to clear rain, snow, or debris from the windshield of a vehicle, which are all common weather-related hazards. The speed at which the wipers move can also indicate the intensity of the precipitation or debris. For instance, if the wipers are moving very fast, it may indicate heavy rain or snow. On the other hand, if the wipers are moving slowly, it could mean that there is only light precipitation. Overall, car wipers are an important safety feature of a vehicle and can help drivers navigate through different weather conditions.

In addition, high beam headlights are considered an indicator of lighting conditions as they are used to provide maximum illumination when driving in low light or dark conditions. The high beam headlights are designed to project a beam of light further down the road, which can help drivers to see obstacles or pedestrians that may be difficult to see with low beam headlights. Overall, high beam headlights are an important feature of a vehicle that can help drivers navigate through different lighting conditions.

***Table 1:** Variables for task complexity and coping capacity (vehicle and operator state) and risk*

Task complexity	Coping capacity – Vehicle State	Coping capacity – operator state		Risk
Car wipers	Vehicle age	Distance	Inter Beat Interval	Headway map levels
Car high beam	First vehicle registration	Duration	Headway	Speeding map levels
Time indicator	Fuel type	Average speed	Overtaking	Overtaking map levels
Distance	Engine Cubic Centimeters	Harsh acceleration/braking	Fatigue	Fatigue map levels
Duration	Engine Horsepower (HP)	Forward collision warning (FCW)	Gender	Harsh acceleration
Month	Gearbox	Pedestrian collision warning (PCW)	Age	Harsh braking
Day of the week	Vehicle brand	Lane departure warning (LDW)	Educational level	Vehicle control events

4. Methodological Overview

4.1 Generalized Linear Models (GLMs)

In statistics, the **Generalized Linear Model** (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value (T. J. Hastie & Pregibon, 2017).

In a generalized linear model (GLM), each outcome Y of the dependent variables is assumed to be generated from a particular distribution in an exponential family, a large class of probability distributions that includes the **normal, binomial, Poisson and gamma distributions**, among others. The mean, μ, of the distribution depends on the independent variables, X, through:

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

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:

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

It is convenient if V follows from an exponential family of distributions, but it may simply be that the variance is a function of the predicted value.

The unknown parameters, β, are typically estimated with maximum likelihood, maximum quasi-likelihood, or Bayesian techniques.

GLMs were formulated as a **way of unifying various other statistical models**, including linear regression, logistic regression, and Poisson regression. In particular, T. Hastie & Tibshirani (1990) 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.

A key point in the development of GLM was the **generalization of the normal distribution** (on which the linear regression model relies) to the exponential family of distributions. This idea was developed by Collins et al. (2001). Consider a single random variable y whose probability (mass) function (if it is discrete) or probability density function (if it is continuous) depends on a single parameter θ. The distribution belongs to the exponential family if it can be written as follows:

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

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

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

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

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

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

4.2 Structural Equation Models (SEM)

Structural Equation Modelling or path analysis is a multivariate method used to test hypotheses regarding the influences among interacting observed and unobserved variables (Harrison et al., 2007). The observed variables are measurable, while unobserved variables are latent constructs.

Structural equation models consist of two components: a measurement model and a structural model. 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. 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 (Washington et al., 2011, 2020):

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

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):

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

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

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.

To depict the structural model, path analysis is often employed, illustrating how a set of "explanatory" variables can influence a "dependent" variable. The paths can be visually represented to indicate whether the explanatory variables are correlated causes, mediated causes, or independent causes of the dependent variable.

4.3 Model goodness-of-fit measures

In the context of model selection, **model Goodness-of-Fit measures** consist 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. A detailed description of the aforementioned metrics is presented below:

The **Akaike Information Criterion (AIC),** which accounts for the number of included independent variables, is used for the process of model selection between models with different combination of explanatory variables (Vrieze, 2012).

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

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

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

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

The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) provide measures of model performance that account for model complexity. AIC and BIC combine a term reflecting how well the model fits the data with a term that penalizes the model in proportion to its number of parameters.

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 (Lee & Sohn, 2022). In general, values more than 0.90 for CFI are generally accepted as indications of very good overall model fit (CFI>0.90). The formula is represented as follows:

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

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

The **Tucker Lewis Index (TLI)** considers the parsimony of the model. Therefore, if the fit indices of two models are similar, a simpler model (i.e. greater degrees of freedom) is chosen. TLISI 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 (Lee & Sohn, 2022). 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:

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

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

Currently, one of the most widely used goodness-of-fit indices is the **Root Mean Square Error Approximation (RMSEA)**. RMSEA measures the unstandardized discrepancy between the population and the fitted model, adjusted by its degrees of freedom (df). Different proposals have been made as to the correct use of RMSEA. The most common approach is to calculate and interpret the sample's RMSEA (McDonald & Ho, 2002). 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:

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

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 **Root Mean Squared Error (RMSE)** is one of the most commonly used measures for evaluating the quality of predictions. It shows how far predictions fall from measured true values using Euclidean distance.

The formula of RMSE, which is the square root of the average squared error, is represented as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum e_t^2} \tag{13}$$

where: N is the number of forecasted points, and e_t is the error (i.e. $observed_t - forecasted_t$)

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 (Baumgartner & Homburg, 1996). 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).

Lastly, the **Hoelter** index is calculated to find if chi-square is insignificant or not. If its value is more than 200 for the model, then model is considered to be good fit with observed data (Hoelter>200). Values of less than 75 indicate very poor model fit. The Hoelter only makes sense to interpret if N > 200 and the chi square is statistically significant.

5. Results

5.1 GLM results

GLMs were employed to investigate the relationship of key performance indicator of speeding for Belgian, UK and German car 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.

The first Generalized Linear Regression model 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 2.

***Table 2:** Parameter estimates and multicollinearity diagnostics of the GLM for speeding*

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.

The second Generalized Linear Regression model investigated the relationship between the speeding and several explanatory variables of task complexity and coping capacity (vehicle and operator state) in UK. More specifically, for task complexity, the variables used are wipers on and high beam, while for coping capacity - operator state, the variables used are distance traveled, duration, harsh acceleration events, gender, forward collision warning and right lane departure warning. It should be noted that for vehicle state, variables such as fuel type, vehicle age and gearbox were not statistically significant; and thus, these independent variables were not included in the analysis. The model parameter estimates are summarized in Table 3.

***Table 3:** Parameter estimates and multicollinearity diagnostics of the GLM for speeding*

Variables	Estimate	Standard Error	z-value	Pr(|z|)	VIF
(Intercept)	-3.824	0.014	-274.620	< .001	-
Duration	4.672×10^{-5}	7.877×10^{-7}	59.317	< .001	1.058
Harsh acceleration	-0.187	0.012	-15.377	< .001	1.014
Weather	-0.273	0.023	-11.713	< .001	1.008
High beam	0.128	0.078	1.635	0.102	1.002
Forward collision warning	10.603	2.479	4.276	< .001	1.001
Right lane departure warning	0.357	0.014	25.348	< .001	1.026
Distance	0.002	1.876×10^{-5}	117.628	< .001	1.072
Gender - Male	0.373	0.012	31.757	< .001	1.056
Summary statistics					
AIC	263599.548				
BIC	263610.743				
Degrees of freedom	537681				

Based on Table 3, it can be observed that all explanatory variables are statistically significant at a 95% confidence level and 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 coping capacity are all positively correlated with speeding except for harsh acceleration events that appear to be fewer when speeding occurs. The opposite happens with FCW and LDW events that appear to be higher in case of speeding. An increase in the trip duration and the distance travelled is associated with an increase in speeding events, as well. The use of wipers though is, as expected, negatively associated with speeding events. Gender was a significant variable in this model showing that male drivers (males coded as 0, females as 1), are possibly prone to speeding while the use of high beams also was connected with higher speeding events possibly due to lighter night hours traffic.

The third Generalized Linear Regression model 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 4.

***Table 4:** Parameter estimates and multicollinearity diagnostics of the GLM for speeding*

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 4, 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 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.

5.2 SEM results

SEM results for phase 1 are shown in Figure 3 below. Risk is measured by means of the STZ levels for speeding, headway, overtaking and fatigue (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).

To begin with, the latent variable task complexity is measured by means of the environmental indicator of time of the day, lighting conditions and weather. Furthermore, it is shown that the latent coping capacity is measured by means of both vehicle state indicators, such as "Vehicle age" (indicating the age of the vehicle), "Gearbox" (indicating the type of gearbox; automatic or manual) and "Fuel type" (indicating the type of fuel; diesel, hybrid electric, petrol). At the same time, operator state indicators, such as "Gender" (indicating the gender of the driver; male or female), "Age" (indicating the age of the driver), distance travelled, harsh acceleration and harsh braking 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=0.02) – which increases in magnitude as the driver's progress from phases 1 though phases 2 and 3. 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=2.17). 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=-0.55).

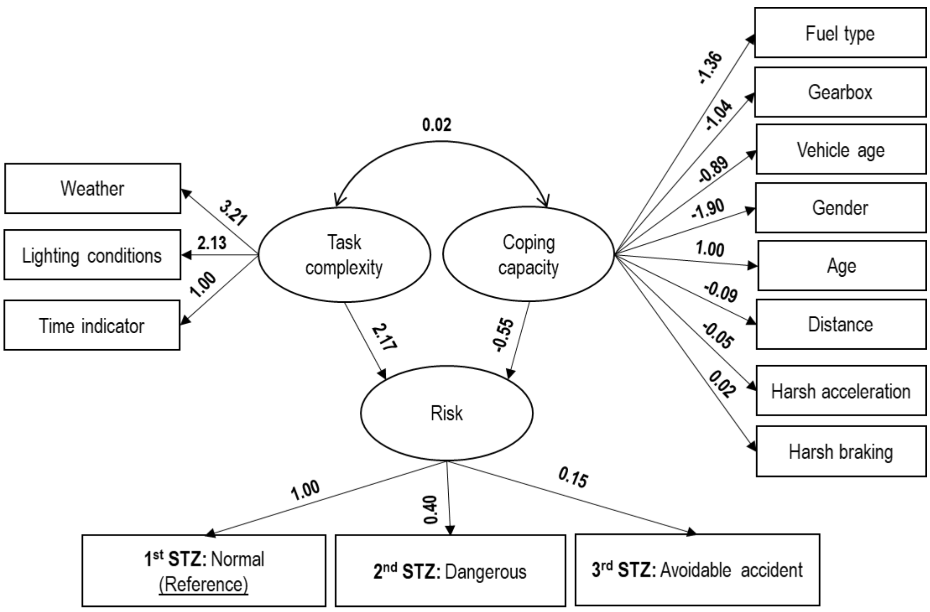

Figure 3: *Results of SEM on Risk (Speeding STZ) – Belgian, German and UK car drivers – experiment Phase 1*

The Comparative Fit Index (CFI) of the model is equal 0.650; TLI is 0.570 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.091. Table 5 summarizes the model fit of SEM applied for speeding.

***Table 5:** Model Fit Summary for speeding-Belgian, German and UK car drivers – experiment Phase 1*

Model Fit measures	Value
AIC	817833.112
BIC	818194.915
CFI	0.650
TLI	0.570
RMSEA	0.091
GFI	0.918
Hoelter's critical N (α = .05)	155.529
Hoelter's critical N (α = .01)	171.977

Residual variances details are presented in Table 6 that follows.

***Table 6:** Residual variances for speeding-Belgian, German and UK car drivers – experiment Phase 1*

Variable	Estimate	Std. Error	z-value	P(>|z|)
Time indicator	0.862	0.009	100.596	< .001
High beam	0.812	0.008	97.405	< .001
Wipers	0.998	0.010	104.686	< .001
Age	0.379	0.009	41.795	< .001
Fuel type	1.000	0.013	76.545	< .001
Vehicle age	1.000	0.013	76.555	< .001
Gearbox	2.402	0.131	18.391	< .001
Distance	1.220	0.023	52.503	< .001
Gender	1.032	0.010	101.735	< .001
Harsh acceleration event high	0.862	0.009	100.596	< .001
STZ1	0.812	0.008	97.405	< .001
STZ2	0.998	0.010	104.686	< .001
STZ3	0.379	0.009	41.795	< .001

The following Figures show the results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of task complexity and coping capacity are fairly 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. The results for phase 2 are shown in Figure 4 below.

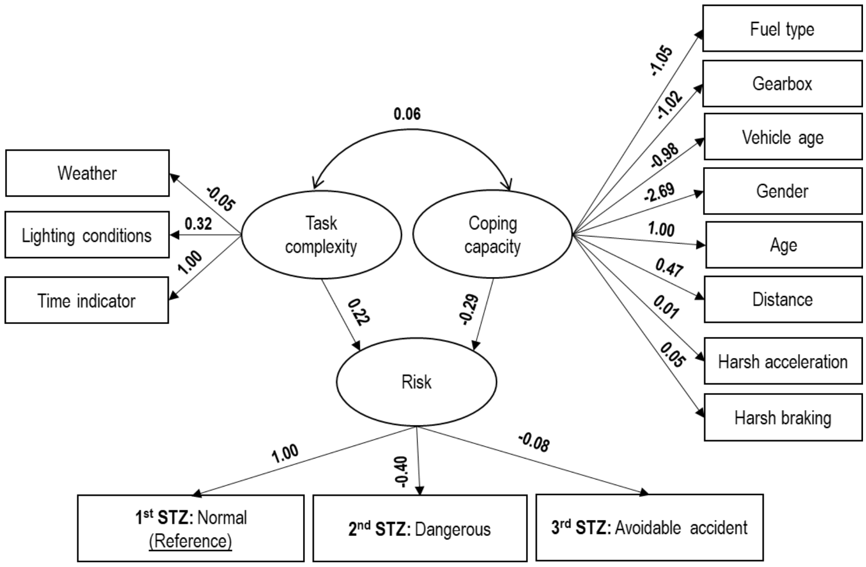

Figure 4: *Results of SEM on Risk (Speeding STZ) – Belgian, German and UK car drivers – experiment Phase 2*

The Comparative Fit Index (CFI) of the model is equal 0.688; TLI is 0.617 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.074. Table 7 summarizes the model fit of SEM applied for speeding.

Table 7: *Model Fit Summary for speeding-Belgian, German and UK car drivers – experiment Phase 2*

Model Fit measures	Value
AIC	$2.512\times10^{+6}$
BIC	$2.512\times10^{+6}$
CFI	0.688
TLI	0.617
RMSEA	0.074
GFI	0.938
Hoelter's critical N (α = .05)	236.232
Hoelter's critical N (α = .01)	261.271

Residual variances details are presented in Table 8 that follows.

***Table 8:** Residual variances for speeding-Belgian, German and UK car drivers – experiment Phase 2*

Variable	Estimate	Std. Error	z-value	P(>|z|)
Time indicator	0.713	0.022	31.963	< .001
High beam	0.970	0.006	171.072	< .001
Wipers	0.999	0.005	187.505	< .001
Age	0.879	0.005	180.312	< .001
Fuel type	0.867	0.005	178.940	< .001
Vehicle age	0.884	0.005	180.930	< .001
Gearbox	0.873	0.005	179.664	< .001
Distance	0.973	0.005	183.467	< .001
Gender	0.120	0.009	13.409	< .001
Harsh acceleration event high	1.000	0.008	123.875	< .001
Harsh breaking event high	1.000	0.008	123.385	< .001
STZ1	-0.361	0.077	-4.690	< .001
STZ2	0.783	0.013	60.557	< .001
STZ3	0.991	0.005	187.483	< .001

The results for phase 3 are shown in Figure 5 below.

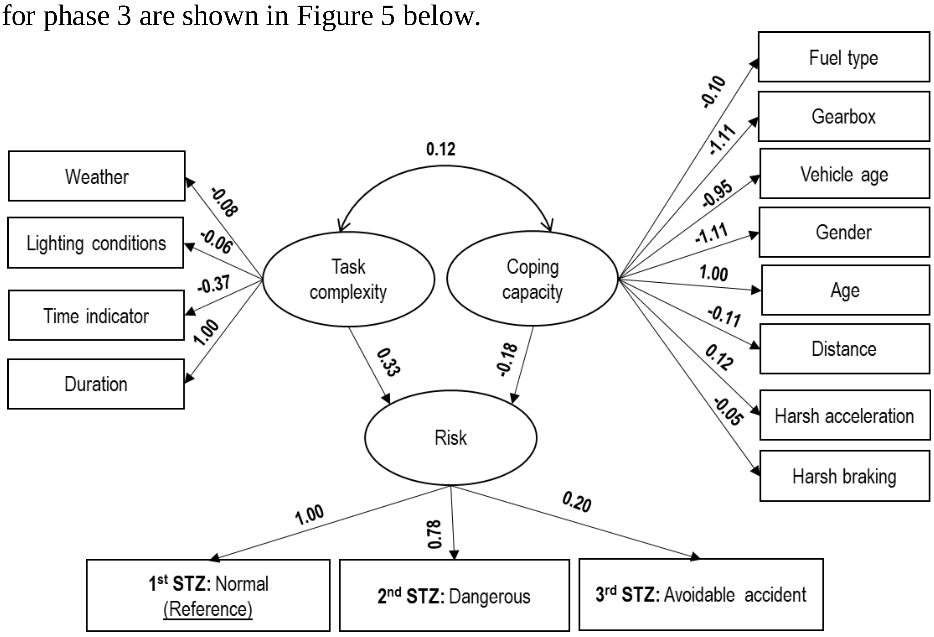

***Figure 5:** Results of SEM on Risk (Speeding STZ) – Belgian, German and UK car drivers – experiment Phase 3*

The Comparative Fit Index (CFI) of the model is equal 0.637; TLI is 0.562 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.087. Table 9 summarizes the model fit of SEM applied for speeding.

***Table 9:** Model Fit Summary for speeding-Belgian, German and UK car drivers – experiment Phase 3*

Model Fit measures	Value
AIC	$2.901\times10^{+6}$
BIC	$2.901\times10^{+6}$
CFI	0.637
TLI	0.562
RMSEA	0.087
GFI	0.908
Hoelter's critical N (α = .05)	166.828
Hoelter's critical N (α = .01)	183.169

Residual variances details are presented in Table 10 that follows.

***Table 10:** Residual variances for speeding-Belgian, German and UK car drivers – experiment Phase 3*

Variable	Estimate	Std. Error	z-value	P(>|z|)
Duration	0.644	0.015	44.245	< .001
Time indicator	0.951	0.005	179.290	< .001
Wipers	0.998	0.005	193.632	< .001
High beam	0.999	0.005	193.861	< .001
Age	0.639	0.004	153.179	< .001
Fuel type	0.997	0.005	195.131	< .001
Vehicle age	0.674	0.004	159.380	< .001
Gearbox	0.557	0.004	135.209	< .001
Distance	0.996	0.005	191.177	< .001
Gender	0.554	0.004	134.476	< .001
Harsh acceleration event high	0.995	0.008	129.345	< .001
Harsh breaking event high	0.999	0.008	129.153	< .001
STZ1	1.629	0.029	56.712	< .001
STZ2	1.386	0.018	75.676	< .001
STZ3	1.026	0.005	188.174	< .001

The results for phase 4 are shown in Figure 6 below.

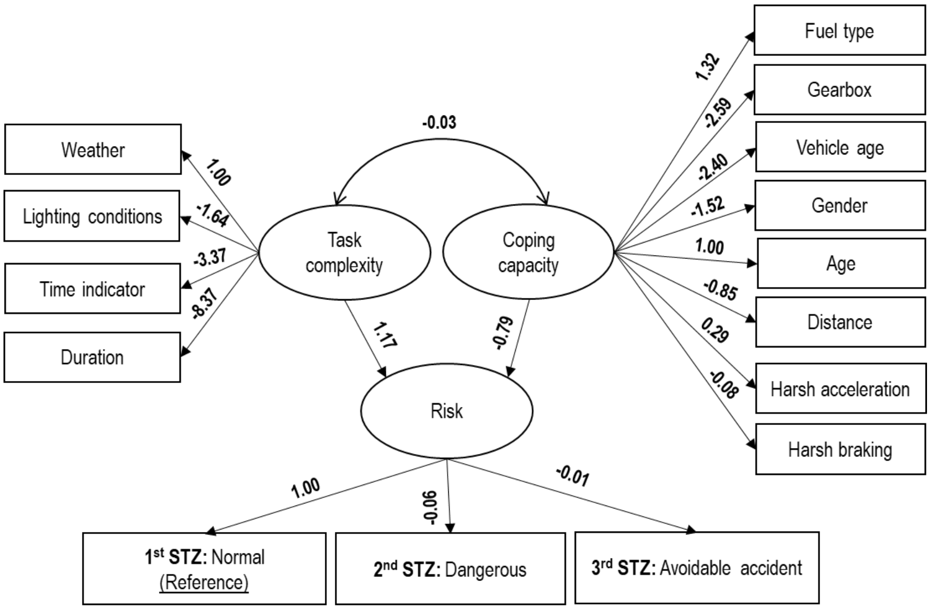

***Figure 6:** Results of SEM on Risk (Speeding STZ) – Belgian, German and UK car drivers – experiment Phase 4*

The Comparative Fit Index (CFI) of the model is equal 0.754; TLI is 0.703 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.093. Table 11 summarizes the model fit of SEM applied for speeding.

***Table 11:** Model Fit Summary for speeding-Belgian, German and UK car drivers–experiment Phase 4*

Model Fit measures	Value
AIC	$5.729\times10^{+6}$
BIC	$5.729\times10^{+6}$
CFI	0.754
TLI	0.703
RMSEA	0.093
GFI	0.899
Hoelter's critical N (α = .05)	147.761
Hoelter's critical N (α = .01)	162.223

Residual variances details are presented in Table 12 that follows.

Table 12: *Residual variances for speeding-Belgian, German and UK car drivers – experiment Phase 4*

Variable	Estimate	Std. Error	z-value	P(>|z|)
Wipers	0.987	0.004	279.552	< .001
High beam	0.966	0.003	278.492	< .001
Duration	0.112	0.006	18.858	< .001
Time indicator	0.855	0.003	265.935	< .001
Age	0.888	0.003	275.077	< .001
Fuel type	0.806	0.003	270.034	< .001
Vehicle age	0.355	0.002	189.990	< .001
Gearbox	0.245	0.002	137.894	< .001
Distance	0.917	0.003	266.204	< .001
Gender	0.742	0.003	265.255	< .001
Harsh acceleration event high	0.995	0.006	168.002	< .001
Harsh breaking event high	1.000	0.006	167.719	< .001
STZ1	-7.362	0.990	-7.435	< .001
STZ2	0.974	0.005	211.023	< .001
STZ3	0.999	0.004	280.639	< .001

6. 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.

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 effectively manage complex tasks, leading to higher crash risk. Reduced coping capacity can manifest as slower reaction times, impaired judgment, and difficulties in prioritizing information. 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.

According to the overall model applied for cars, the latent variable risk was measured by means of the STZ levels for speeding, headway, overtaking and fatigue. The positive correlation of task complexity and coping capacity implied that drivers' coping capacity increased as the complexity of driving task increases. This finding may be a sign of risk compensating behavior of drivers when the complexity of driving task is high, and is in line with the theoretical model of i-DREAMS, validating the assumption that risk (or its' inverse, the normal driving) is an outcome of the interaction between the two variables in addition to their separate effect. A positive correlation of risk with the STZ indicators was identified in phase 1, while a negative correlation was found in phase 4 which showed that the latent variable risk could in fact be representing an inverse of risk, more like a normal driving.

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 effectively manage 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 in this work 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.

7. Conclusions

The objective of the present research was to model the inter-relationship between driving task complexity, coping capacity and crash risk using the i-DREAMS database. For that purpose, data collected from a naturalistic driving experiment with a sample of 130 drivers were utilized and data from Belgian, German and UK car 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.

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 that the SEM applied between 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. Driving task complexity refers to the level of demand and cognitive load imposed on the driver by various factors such as traffic density, road conditions, weather, and the presence of distractions. Coping capacity, on the other hand, encompasses the individual driver's ability to effectively manage and adapt to these complex driving tasks. It includes factors like driver experience, skills, perceptual abilities, decision-making processes, and the availability of appropriate coping strategies. 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.

It is also crucial to address the factors that contribute to road crashes, such as speeding, distracted driving, impaired driving, and failure to follow traffic rules. By promoting responsible driving behavior and creating awareness about the potential consequences of these actions, we can significantly reduce the occurrence of crashes. Additionally, providing proper education and training to drivers, especially young and inexperienced ones, can instill good driving habits and improve overall road safety. Implementing effective road safety measures requires a collaborative effort from governments, law enforcement agencies, transportation authorities, and the community as a whole. Together, we can create a safer road environment that prioritizes the well-being and lives of all road users.

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.

Acknowledgements

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).

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