How do task complexity and coping capacity influence risk? Findings from a novel naturalistic driving experiment in Greece

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Abstract

The i-DREAMS project developed a Safety Tolerance Zone (STZ) to define the point of safe self-regulated control, taking into account the significant impact of the human factor on safe driving behavior. This research aims to analyze the impact of critical factors like task complexity and coping capacity on risk. A naturalistic driving experiment was conducted in Greece, utilizing raw data from thousands of trips by representative drivers. Results showed that demographic characteristics, such as gender and age, correlated negatively with coping capacity, indicating lower levels in male and elderly drivers. Factors like vehicle age, fuel type, and trip difficulty increased task complexity. Coping capacity and task complexity were strongly correlated with driving risk. This paper will provide policy recommendations for implementing the i-DREAMS platform to improve road safety in these areas.

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

Περίληψη

Το έργο i-DREAMS ανέπτυξε μια ζώνη ανοχής ασφάλειας (STZ) για τον καθορισμό του σημείου ασφαλούς αυτορυθμιζόμενου ελέγχου, λαμβάνοντας υπόψη τη σημαντική επιρροή του ανθρώπινου παράγοντα στην ασφαλή οδηγική συμπεριφορά. Η παρούσα έρευνα αποσκοπεί στην ανάλυση της επίδρασης κρίσιμων παραγόντων όπως η δυσκολία στο έργο της οδήγησης και η ικανότητα αντιμετώπισης του κινδύνου. Ένα πείραμα σε πραγματικές συνθήκες οδήγησης διεξήχθη στην Ελλάδα και χρησιμοποιήθηκαν δεδομένα από χιλιάδες διαδρομές. Τα αποτελέσματα έδειξαν ότι τα δημογραφικά χαρακτηριστικά (όπως φύλο, ηλικία) συσχετίστηκαν αρνητικά με την ικανότητα αντιμετώπισης, υποδεικνύοντας χαμηλότερα επίπεδα στους άνδρες και τους ηλικιωμένους οδηγούς. Παράγοντες όπως η ηλικία του οχήματος, ο τύπος καυσίμου και η δυσκολία του ταξιδιού αύξησαν την δυσκολία στο έργο της οδήγησης. Η ικανότητα αντιμετώπισης και η πολυπλοκότητα των καθηκόντων συσχετίστηκαν έντονα με τον οδηγικό κίνδυνο. Η μελέτη θα παρέχει συστάσεις πολιτικής για την εφαρμογή της πλατφόρμας i-DREAMS για τη βελτίωση της οδικής ασφάλειας σε αυτές τις περιοχές.

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

1. Introduction

Every year, the lives of approximately 1.3 million people are cut short as a result of a road traffic crash. Between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury (World Health Organization, 2022). Driver behavior plays a significant role in over 90 percent of these crashes (Ivers et al., 2009). Consequently, there is immense value in identifying drivers who engage in unsafe practices, as they pose a greater risk to themselves and other road users. Various approaches have been employed for this purpose, including the development of demographic profiles (Wundersitz & Hutchinson, 2008), self-reported behavior and risk preferences (Pajković & Grdinić-Rakonjac, 2021), as well as assessments of personality and risk perceptions (Zhang et al., 2020).

Based on the abovementioned, the primary objective of the European Horizon2020 i-DREAMS project is to define, develop, test, and validate a ‘Safety Tolerance Zone (STZ)’ to keep drivers within acceptable boundaries of safe operation. By continuously monitoring risk factors associated with task complexity (such as traffic conditions and weather) and coping capacity (including the driver's mental state, driving behavior, and vehicle status), i-DREAMS aims to ensure safe driving behavior by triggering real-time and post trip interventions.

The STZ is divided into three separate levels according to the level of risky driving behavior (i.e. ‘Normal’, ‘Dangerous’ and ‘Avoidable Accident’). Firstly, the ‘Normal’ level refers to the scenario of low crash risk and therefore safe driving behavior. Secondly, the ‘Dangerous’ level concerns the increased likelihood of crash occurrence, however the crash is not inevitable. Lastly, the ‘Avoidable Accident’ level indicates a strong likelihood of a potential crash happening, yet there remains sufficient time for drivers to act and prevent the collision.

Specifically, the in-vehicle interventions are meant to assist and support vehicle operators in real-time (i.e., while driving). Depending on how imminent crash risks are, a distinction can be made between a ‘normal driving’ phase, a ‘danger’ phase, and an ‘avoidable accident’ phase. In the normal driving phase, no abnormalities in a vehicle operator’s driving style are detected by the monitoring pillar of the i-DREAMS platform, and no sign of a crash course initiating is present. Consequently, no real-time intervention is required. In the danger phase, abnormal deviations from the vehicle operator’s driving style are detected by the i-DREAMS monitoring module, and the potential for a crash course to unfold is present. A warning signal is to be issued in that case. In the avoidable accident phase, deviations from normal driving have evolved even further, and the risk for a crash to occur will become imminent if the vehicle operator does not adapt appropriately and immediately to the present circumstances. A more intrusive warning signal is provided to support vehicle operators in avoiding a collision.

With regards to post-trip interventions, these are not operational while driving, but they are based on what happens during a trip. They hinge upon all the raw data that is captured by the i-DREAMS sensors, which is further processed and fused into information about a vehicle operator’s driving style, how it evolved during a trip, how many (safety-critical) events occurred, and in which circumstances these events happened. This information can be further translated into feedback consultable for vehicle operators via an app in a pre- or post-trip setting. To establish a longer-term relationship with individual vehicle operators, app-supported feedback can be combined with the use of a web-based coaching platform, containing gamification features meant to motivate drivers to work on a gradual and persistent improvement of their driving.

Following the objective of the i-DREAMS project, this study aims to examine the impact of task complexity and coping capacity on risk. To achieve this goal, it is necessary to extract a comprehensive set of quantitative effects of indicators, describing the impacts of vehicle, operator, and context characteristics on risk under different conditions. Therefore, an integrated model is applied to gain an in-depth understanding of inter-relationship with risk.

The paper is structured as follows. At the beginning, a detailed description of the project and its general objective is provided. Subsequently, an extensive literature review is presented concerning the analysis of driving behavior utilizing statistical methods. In addition, the data collection process is thoroughly presented. The research methodology is then described, which includes the theoretical background of the models used. Finally, the results are presented and are followed with significant conclusions about the relationship between critical factors such as task complexity and coping capacity on risk.

2. Definitions

2.1 Task complexity

The cornerstone of the i-DREAMS platform is the assessment of task complexity and coping capacity. Task complexity relates to the current status of the real-world context in which a vehicle is being operated. Since this context is consistent of various individual elements which, together, determine the complexity of the task imposed on the vehicle operator, a multi-dimensional approach in further operationalizing this concept is adopted. In particular, task complexity context is monitored via registration of road layout (i.e., highway, rural, urban), time and location, traffic volumes (i.e. high, medium, low) and weather.

2.2 Coping capacity

As for coping capacity, Figure 1 shows that this concept is dependent upon two underlying factors and it consists of several aspects of both vehicle and operator state. These are also multi-dimensional in nature.

More specifically, the latent variables associated to “vehicle state” are estimated on the basis of various metrics. The factor ‘vehicle’ entails three aspects, as shown below:

- Technical specifications, measured on the basis of average speed, braking power, acceleration performance, etc.
- Actuators & admitted actions, measured on the basis of accelerator, brakes, steering wheel, 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 ADAS systems - (headway & collision monitoring, pedestrian warning, lane keeping monitoring, on board cameras, etc.

Additionally, the latent variables associated to “operator state” are estimated on the basis of various metrics. The factor ‘operator’ entails six aspects, as shown below:

- Mental state, measured on the basis of 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 on the basis of metrics on risk assessment, attention regulation, self-appraisal, etc.

- Personality, measured on the basis of metrics on adventure seeking, disinhibition, experience seeking, boredom susceptibility, etc.
- Sociodemographic profile, measured on the basis of age, gender, experience, socio-economic status, nationality, ethnicity, cultural identity, etc.
- Health status, measured on the basis of metrics on current symptoms, neurologic and cardiovascular indicators, medication, etc.

As already outlined, coping capacity is not only dependent upon the status of the operator, but of the vehicle as well. Each of these operator- and vehicle-related aspects can be further operationalized by a combination of different variables, as shown in Figure 1.

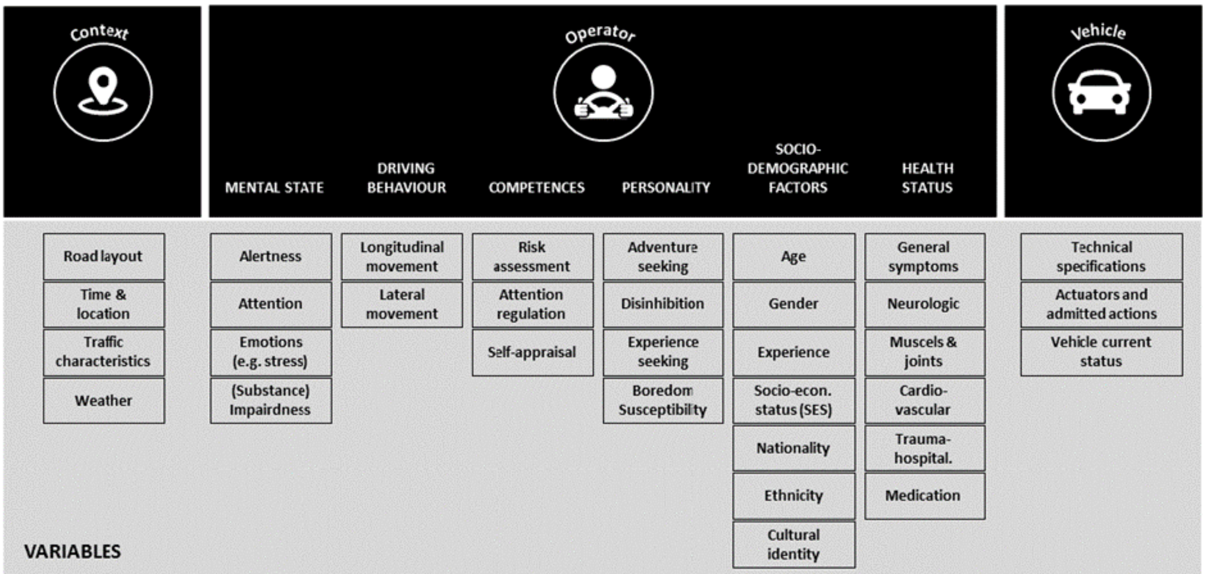

***Figure 1:** Monitoring context, operator & vehicle: an illustrative canvas*

3 Literature Review

Road safety is a critical area of concern worldwide, with road crashes causing significant human casualties and economic losses. In recent years, researchers and policymakers have increasingly turned to advanced statistical modelling techniques to gain a deeper understanding of the complex factors influencing road safety outcomes. One such technique that has gained popularity in this domain is the application of Structural Equation Models (SEMs).

SEMs are a powerful statistical tool that allows researchers to examine the relationships between latent variables and observed variables, separating measurement errors from true scores of attributes (Yuan & Bentler, 2006). Unlike traditional regression models, SEMs not only estimate the direct effects of variables but also provide a framework for exploring the indirect effects and mediating relationships among variables. By employing SEMs, researchers can assess the complex interplay of various factors and their impacts on road safety outcomes, providing valuable insights for the development of effective intervention strategies and policy measures.

The use of SEMs in road safety research has numerous advantages. Firstly, SEMs can capture the multidimensional nature of road safety phenomena by incorporating multiple observed variables and latent constructs. This enables researchers to account for the inherent complexity of road safety, which involves various factors such as driver behaviour, vehicle characteristics, road conditions, and environmental factors. For example, research has shown that factors related to road, driver, and environment had a significant influence on crash size (J.-Y. Lee et al., 2008). By considering these interrelated factors simultaneously, SEMs offer a holistic perspective on the underlying mechanisms driving road safety outcomes.

Secondly, SEMs allow for the examination of causal relationships among variables. This is particularly valuable in road safety research, where understanding causal pathways is essential for designing targeted interventions. Studies have examined the relationship between risky driving behaviour with gender, anxiety, reward sensitivity, and sensation-seeking propensity (Scott-Parker et al., 2013). SEMs facilitate the identification of direct and indirect effects, mediating variables, and moderating factors, thereby unravelling the intricate relationships that contribute to road safety outcomes.

Furthermore, SEMs provide a means to validate theoretical frameworks and models in the road safety domain. By comparing observed data with hypothesized relationships, researchers can assess the goodness-of-fit of their models and refine them accordingly. This iterative process of model development and refinement enables the creation of robust frameworks that accurately represent the underlying dynamics of road safety. For instance, studies have analysed the correlation between crash occurrence with risk indicators using SEMs (Shah et al., 2018)

In conclusion, SEMs have emerged as a powerful analytical tool in road safety research. Their ability to capture complex relationships, explore causal pathways, and validate theoretical frameworks makes them a valuable asset in the pursuit of improved road safety outcomes. By leveraging the insights provided by SEMs, researchers and policymakers can work towards the development of effective strategies that minimize traffic crashes, reduce injuries, and save lives on our roadways.

4. Data Collection

4.1 Experiment description

As part of the i-DREAMS project, a naturalistic driving experiment was conducted in Greece involving 65 car drivers and a large database of 9,066 trips and 161,443 minutes was created. Moreover, data from an additional telematics experiment which took place for a 3-month timeframe were collected and analyzed in order to enhance the power of the analyses presented. The on-road trial experiment was carried out in three phases (i.e., phase 1 – monitoring, phase 2 - real-time intervention and post-trip feedback and phase 3 - real-time intervention and post-trip feedback and gamification).

In addition, to the vehicle data, questionnaire data were collected both before and after the trial.
Information collected pre-trial included:

- Screening questionnaire: driver details (age, gender, driving experience, employment status, etc.), vehicle details (model, age, etc.).
- Entry questionnaire: current use of and opinions on different ADAS, driving style and confidence, opinions on driving and safety, self-assessment of driver’s risk-taking behaviors (e.g., speeding, mobile phone use), crash and offence history, sleepiness and driving, medical conditions.

Information collected post-trial included:

- User experience questionnaire: opinions on the i-DREAMS system - except for Greece, in which an alternative driving experiment without the use of i-DREAMS in-vehicle system was used - (ease of use, works as described), opinions on the i-DREAMS smartphone app (ease of use, usefulness).
- Exit questionnaire: opinions on the i-DREAMS system (improvement of driving, usefulness, trust, clarity of warnings, etc.), experience of driving situations, driver behavior (driving and non-driving related behaviors), overall experience rating.

4.2 Variables used

The primary obstacle of the i-DREAMS project involves establishing the correlation between explanatory variables, such as different performance metrics and indicators of task complexity and coping capacity, with the dependent variable "risk," to effectively predict STZ.

There are three main components of the nature of variables which are used in i-DREAMS:

- Discrete variables: variables that are categorical (ordinal or nominal) and can only take discrete values from the real numbers. A few examples of discrete variables in i-DREAMS could be fatigue (yes, no), time of the day (daytime, nighttime driving) and STZ (normal phase, danger phase, avoidable accident phase).
- Continuous variables: variables that can take any values from the real numbers. A few examples of continuous variables in i-DREAMS could be speeding, headway and composite variables, such as weighted sum or weighted average variables.
- Latent variables: variables that are not observable to the analyst and so it is not known whether they are continuous or discrete. Examples of latent variables in i-DREAMS are task complexity and coping capacity which are latent explanatory variables and so observable indicators are needed to measure these latent variables. Risk is also initially conceived in i-DREAMS as a latent variable.

5. Methodology

5.1 Structural Equation Models (SEMs)

SEM is widely used for modelling complex and multi-layered relationships between observed and unobserved variables, such as ‘task complexity’ etc. Observed variables are measurable, whereas unobserved variables are latent constructs – analogous to factors or components in a factor / principal component analysis.

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

The general formulation of SEM is as follows (Washington et al., 2011, 2020):

$$\eta = \beta\eta + \gamma\xi + \varepsilon \quad \textbf{(1)}$$

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

The measurement models are then as follows (Chen, 2007):

$$x = \Lambda x\xi + \delta, \text{ for the exogenous variables} \quad \textbf{(2)}$$

$$y = \Lambda y\eta + \zeta, \text{ for the endogenous variables} \quad \textbf{(3)}$$

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

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

5.2 Model performance

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).

$$AIC = -2L(\theta) + q \quad \textbf{(4)}$$

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.

$$BIC = -2L(\theta) + q\ln(N) \quad \textbf{(5)}$$

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:

$$CFI = 1 - \frac{\max(x_H{}^2 - df_H, 0)}{\max(x_H{}^2 - df_H, x_I{}^2 - df_I)} \tag{6}$$

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:

$$TLI = \frac{\frac{x_I{}^2}{df_I} - \frac{x_H{}^2}{df_H}}{\frac{x_I{}^2}{df_I} - 1} \tag{7}$$

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:

$$RMSEA = \sqrt{\frac{x_H{}^2 - df_H}{df_H(n-1)}} \tag{8}$$

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:

$$RMSE = \sqrt{\frac{1}{N}\sum e_t^2} \quad \textbf{(9)}$$

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.

6. Results

Three separate SEM models were estimated in order to explore the relationship between the latent variables of task complexity, coping capacity and risk (expressed as the three phases of the STZ) of speeding. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 65 Greek car drivers, 2,937 trips (51,786 minutes)
- Phase 2: real-time & post-trip interventions - 65 Greek car drivers, 3,935 trips (69,962 minutes)
- Phase 3: real-time. post-trip interventions & gamification - 65 Greek car drivers, 2,194 trips (39,695 minutes)

6.1 Task complexity analysis

The results concerning the impact of task complexity on risk, for phase 1, are shown in Figure 2 below. Risk is measured by means of the STZ levels for speeding (level 1 refers to ‘normal driving’ used as the reference case, level 2 refers to ‘dangerous driving’ while level 3 refers to ‘avoidable accident driving’), with positive correlations of Risk with the STZ indicators.

To begin with, the latent variable task complexity is measured by means of the environmental indicators “Time indicator” (indicating time of the day). The exposure indicator of trip duration was also included in the task complexity analysis.

Overall, the structural model between task complexity and risk shows a positive but negligible coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=0.05).

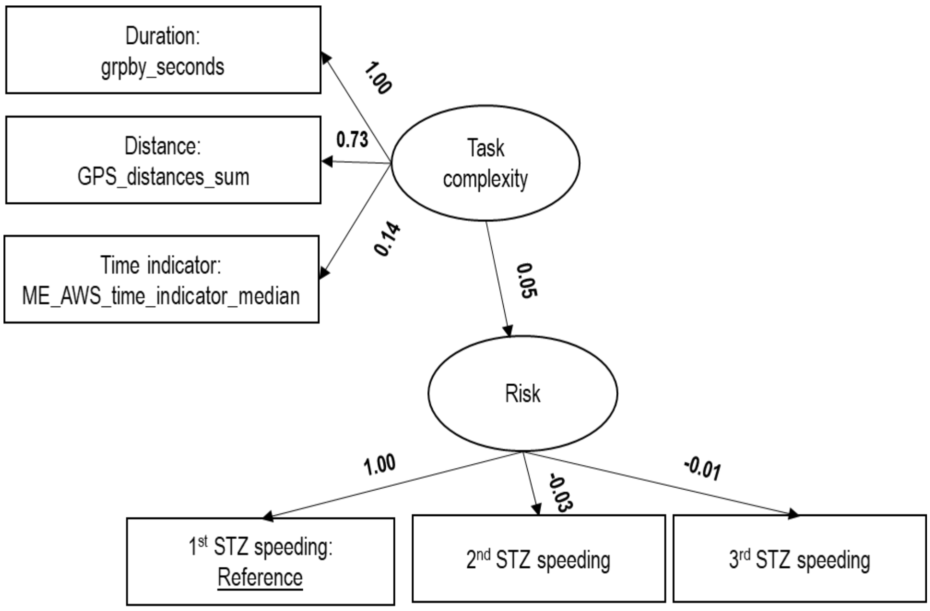

***Figure 2:** Results of SEM of task complexity on risk (speeding STZ) – experiment Phase 1*

The Comparative Fit Index (CFI) of the model is equal to 0.967; TLI is 0.939 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.091. Table 1 summarizes the model fit of SEM applied for speeding.

***Table 1:** Model Fit Summary for speeding – experiment Phase 1*

Model Fit Summary	
AIC	314702.148
BIC	314854.909
CFI	0.967
TLI	0.939
RMSEA	0.091
GFI	0.975
Hoelter's critical N (α = .05)	232.504
Hoelter's critical N (α = .01)	300.920

Residual variances details are presented in Table 2 that follows.

***Table 2:** Residual variances for speeding – experiment Phase 1*

Variable	Estimate	Std. Error	z-value	p
Duration	0.783	0.054	14.508	< .001
Distance	0.885	0.029	30.050	< .001
Time indicator	0.996	0.009	105.704	< .001
Speeding level 0	-33.128	43.663	-0.759	0.448
Speeding level 1	0.975	0.033	29.423	< .001
Speeding level 2	0.967	0.010	94.075	< .001

The following Figures show the results of the 2nd and 3rd 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 three phases. The results for phase 2 are shown in Figure 3 below.

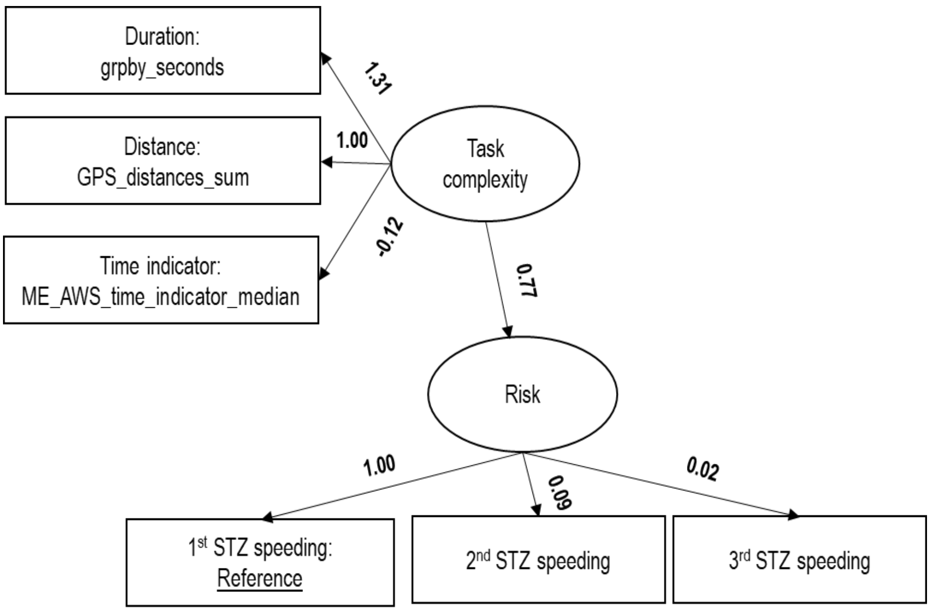

Figure 3: *Results of SEM of task complexity on risk (speeding STZ) – experiment Phase 2*

The Comparative Fit Index (CFI) of the model is equal to 0.960; TLI is 0.925 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.088. Table 3 summarizes the model fit of SEM applied for speeding.

Table 3: *Model Fit Summary for speeding – experiment Phase 2*

Model Fit Summary	
AIC	$1.052 \times 10^{+6}$
BIC	$1.052 \times 10^{+6}$
CFI	0.960
TLI	0.925
RMSEA	0.088
GFI	0.975
Hoelter's critical N (α = .05)	248.125
Hoelter's critical N (α = .01)	321.159

Residual variances details are presented in Table 4 that follows.

Table 4: *Residual variances for speeding – experiment Phase 2*

Variable	Estimate	Std. Error	z-value	p
Distance	0.928	0.006	157.921	< .001
Duration	0.877	0.007	120.516	< .001
Time indicator	0.999	0.005	193.616	< .001
Speeding level 0	10.802	2.145	5.035	< .001
Speeding level 1	1.078	0.018	59.878	< .001
Speeding level 2	0.960	0.006	161.128	< .001

The results for phase 3 are shown Figure 4 below.

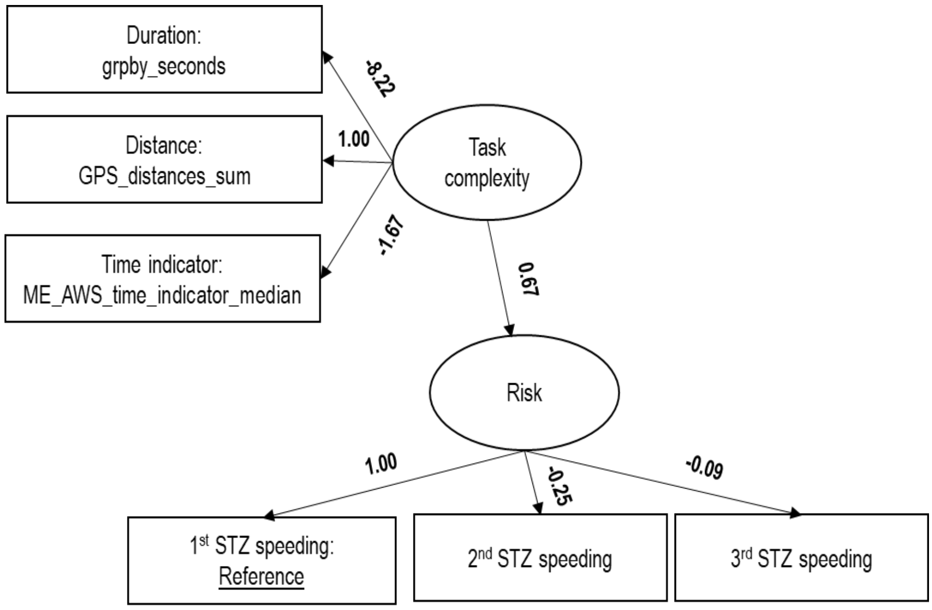

***Figure 4:** Results of SEM of task complexity on risk (speeding STZ) – experiment Phase 3*

The Comparative Fit Index (CFI) of the model is equal to 0.918, TLI is 0.847 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.134. Table 5 summarizes the model fit of SEM applied for speeding.

***Table 5:** Model Fit Summary for speeding – experiment Phase 3*

Model Fit Summary	
AIC	$2.028\times10^{+6}$
BIC	$2.028\times10^{+6}$
CFI	0.918
TLI	0.847
RMSEA	0.134
GFI	0.943
Hoelter's critical N (α = .05)	108.695
Hoelter's critical N (α = .01)	140.523

Residual variances details are presented in Table 6 that follows.

***Table 6:** Residual variances for speeding – experiment Phase 3*

Variable	Estimate	Std. Error	z-value	p
Distance	0.971	0.004	263.800	< .001
Duration	-0.759	0.059	-12.949	< .001
Time indicator	0.927	0.004	227.104	< .001
Speeding level 0	-2.551	0.096	-26.536	< .001
Speeding level 1	0.783	0.007	117.887	< .001
Speeding level 2	0.927	0.004	219.034	< .001

6.2 Coping capacity (vehicle and operator state) analysis

The results of the effect of coping capacity on risk for phase 1 are shown in Figure 5 below. Risk is measured by means of the STZ levels for speeding (level 1 refers to ‘normal driving’ used as the reference case, level 2 refers to ‘dangerous driving’ while level 3 refers to ‘avoidable accident driving’), with positive correlations of Risk with the STZ indicators.

First of all, the latent coping capacity is measured by means of operator state indicators, such as duration, distance, harsh acceleration, harsh braking, age and gender. At the same time, the indicators of coping capacity - vehicle state, such as Vehicle age, gearbox or fuel type are included in the SEM applied.

Overall, 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=-0.26).

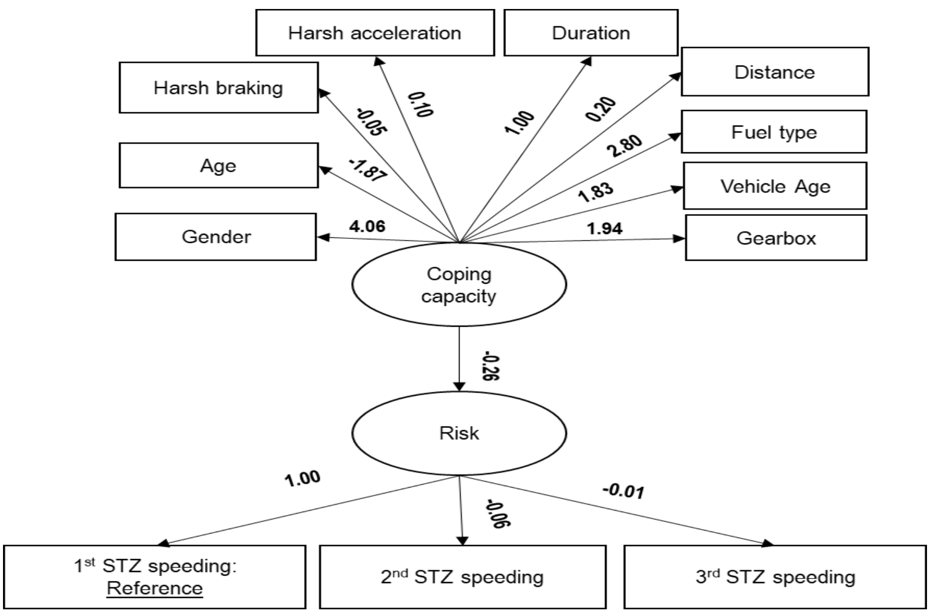

***Figure 5:** Results of SEM of coping capacity on risk (speeding STZ) – experiment Phase 1*

The Comparative Fit Index (CFI) of the model is equal 0.850; TLI is 0.813 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.092. Table 7 summarizes the model fit of SEM applied for speeding.

Table 7: *Model Fit Summary for speeding – experiment Phase 1*

Model Fit Summary	
AIC	627917.827
BIC	628215.310
CFI	0.850
TLI	0.813
RMSEA	0.092
GFI	0.925
Hoelter's critical N (α = .05)	156.811
Hoelter's critical N (α = .01)	176.234

Residual variances details are presented in Table 8 that follows.

Table 8: *Residual variances for speeding – experiment Phase 1*

Variable	Estimate	Std. Error	z-value	p
Duration	0.959	0.009	105.572	< .001
Distance	0.998	0.010	104.690	< .001
Harsh acceleration	1.000	0.013	76.548	< .001
Age	0.855	0.008	100.639	< .001
Gender	0.317	0.010	31.772	< .001
Fuel type	0.674	0.008	84.382	< .001
Vehicle age	0.862	0.009	101.024	< .001
Gearbox	0.843	0.008	99.927	< .001
Harsh breaking	1.000	0.013	76.555	< .001
Speeding level 0	-14.334	8.264	-1.735	0.083
Speeding level 1	0.945	0.031	30.328	< .001
Speeding level 2	0.966	0.010	94.063	< .001

The following Figures show the results of the 2nd and 3rd phase of the experiment. It is observed that the measurement equations of 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 while coping capacity and inverse risk (normal driving) are negatively correlated among the three phases. The results for phase 2 are shown in Figure 6 below.

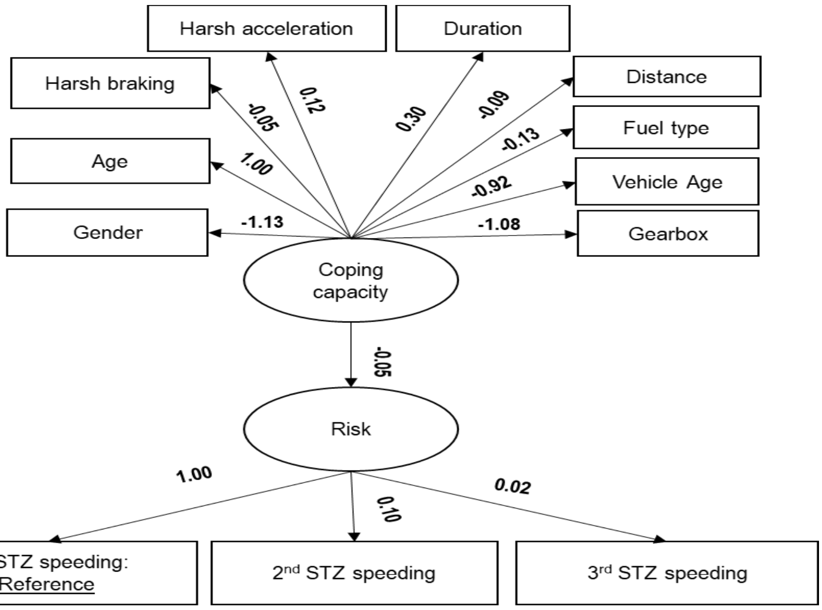

***Figure 6:** Results of SEM of coping capacity on risk (speeding STZ) – experiment Phase 2*

The Comparative Fit Index (CFI) of the model is equal 0.815; TLI is 0.769 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.098. Table 9 summarizes the model fit of SEM applied for speeding.

***Table 9:** Model Fit Summary for speeding – experiment Phase 2*

Model Fit Summary	
AIC	$2.057\times10^{+6}$
BIC	$2.058\times10^{+6}$
CFI	0.815
TLI	0.769
RMSEA	0.098
GFI	0.903
Hoelter's critical N (α = .05)	141.664
Hoelter's critical N (α = .01)	159.199

Residual variances details are presented in Table 10 that follows.

***Table 10:** Residual variances for speeding – experiment Phase 2*

Variable	Estimate	Std. Error	z-value	p
Age	0.632	0.004	151.404	< .001
Distance	0.997	0.005	191.286	< .001
Duration	0.966	0.005	192.843	< .001
Gender	0.532	0.004	128.544	< .001
Fuel type	0.994	0.005	194.944	< .001
Vehicle age	0.687	0.004	161.350	< .001
Gearbox	0.572	0.004	138.444	< .001
Harsh breaking	0.999	0.008	129.154	< .001
Harsh acceleration	0.995	0.008	129.345	< .001
Speeding level 0	9.928	1.890	5.253	< .001
Speeding level 1	1.085	0.019	57.401	< .001
Speeding level 2	0.960	0.006	160.597	< .001

The results for phase 3 are shown in Figure 7 below.

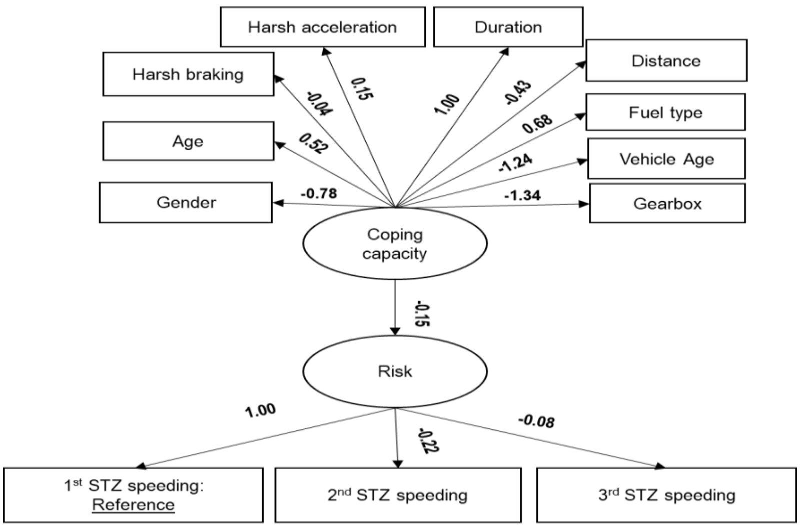

***Figure 7:** Results of SEM of coping capacity on risk (speeding STZ) – experiment Phase 3*

The Comparative Fit Index (CFI) of the model is equal 0.816, TLI is 0.774 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.115. Table 11 summarizes the model fit of SEM applied for speeding.

***Table 11:** Model Fit Summary for speeding – experiment Phase 3*

Model Fit Summary	
AIC	$3.902 \times 10^{+6}$
BIC	$3.903 \times 10^{+6}$
CFI	0.816
TLI	0.771
RMSEA	0.115
GFI	0.869
Hoelter's critical N (α = .05)	102.409
Hoelter's critical N (α = .01)	115.051

Residual variances details are presented in Table 12 that follows.

***Table 12:** Residual variances for speeding – experiment Phase 3*

Variable	Estimate	Std. Error	z-value	p
Duration	0.579	0.002	247.029	< .001
Distance	0.921	0.003	266.306	< .001
Harsh acceleration	0.995	0.006	168.010	< .001
Age	0.886	0.003	274.877	< .001
Gender	0.740	0.003	264.872	< .001
Fuel type	0.806	0.003	269.842	< .001
Vehicle age	0.355	0.002	188.034	< .001
Gearbox	0.247	0.002	136.651	< .001
Harsh breaking	1.000	0.006	167.717	< .001
Speeding level 0	-2.915	0.126	-23.181	< .001
Speeding level 1	0.805	0.007	114.329	< .001
Speeding level 2	0.925	0.004	217.575	< .001

6.3 Synthesis of risk factors

The results of the influence of the risk indicators (i.e., task complexity and coping capacity) for phase 1 are shown in Figure 8 below. Risk is measured by means of the STZ levels for speeding (level 1 refers to 'normal driving' used as the reference case, level 2 refers to 'dangerous driving' while level 3 refers to 'avoidable accident driving'), with positive correlations of Risk with the STZ indicators.

To begin with, the latent variable task complexity is measured by means of the environmental indicators "Time indicator" (indicating time of the day). The exposure indicator of trip duration was also included in the task complexity analysis. In particular, time of the day and duration had a positive correlation with task complexity. Moreover, the latent coping capacity is measured by means of operator state indicators, such as distance, harsh acceleration, harsh braking, age and gender. At the same time, the indicators of coping capacity - vehicle state, such as Vehicle age, gearbox or fuel type are included in the SEM applied.

The structural model between the latent variables shows some interesting findings. First of all, task complexity and coping capacity are inter-related with a positive correlation (regression coefficient=0.56). 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=0.69). 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=-0.35).

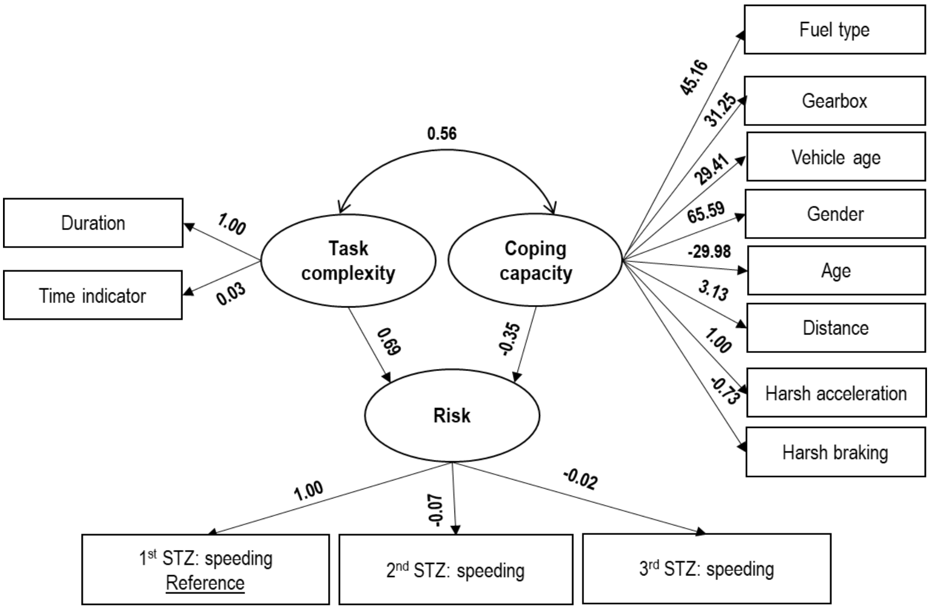

Figure 8: *Results of SEM on risk (speeding STZ) – Greek car drivers – experiment Phase 1*

The Comparative Fit Index (CFI) of the model is equal 0.840; TLI is 0.798 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.089. Table 13 summarizes the model fit of SEM applied for speeding.

Table 13: *Model Fit Summary for speeding – Greek car drivers – experiment Phase 1*

Model Fit Summary	
AIC	692252.677
BIC	692590.360
CFI	0.840
TLI	0.798
RMSEA	0.089
GFI	0.925
Hoelter's critical N (α = .05)	164.309
Hoelter's critical N (α = .01)	183.214

Residual variances details are presented in Table 14 that follows.

Table 14: *Residual variances for speeding – Greek car drivers – experiment Phase 1*

Variable	**Estimate**	**Std. Error**	**z-value**	**p**
Duration	-13.639	52.128	-0.262	0.794
Distance	0.998	0.011	89.383	< .001
Time indicator	1.000	0.009	106.909	< .001
Harsh acceleration	1.000	0.013	76.550	< .001
Age	0.862	0.009	101.232	< .001
Gender	0.299	0.010	29.136	< .001
Fuel type	0.674	0.008	84.400	< .001
Vehicle age	0.864	0.009	101.297	< .001
Gearbox	0.849	0.008	100.479	< .001
Harsh breaking	1.000	0.013	76.556	< .001
Speeding level 0	-9.548	3.697	-2.583	0.010
Speeding level 1	0.920	0.030	31.114	< .001
Speeding level 2	0.964	0.010	94.063	< .001

The following Figures show the results of the 2nd and 3rd 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 three 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 9 below.

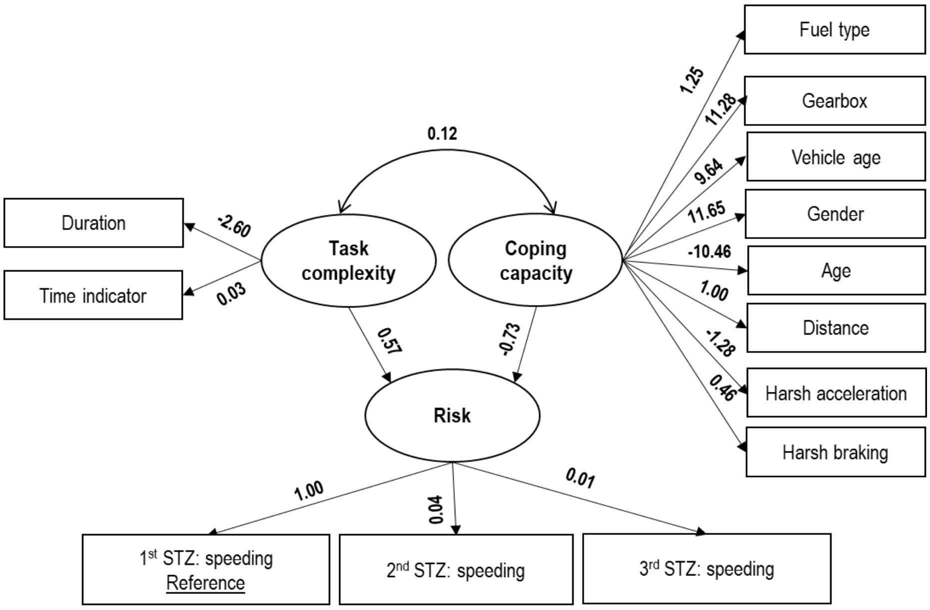

Figure 9: *Results of SEM on risk (speeding STZ) – Greek car drivers – experiment Phase 2*

The Comparative Fit Index (CFI) of the model is equal 0.811; TLI is 0.762 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.092. Table 15 summarizes the model fit of SEM applied for speeding.

Table 15: *Model Fit Summary for speeding – Greek car drivers – experiment Phase 2*

Model Fit Summary	
AIC	$2.268 \times 10^{+6}$
BIC	$2.268 \times 10^{+6}$
CFI	0.811
TLI	0.762
RMSEA	0.092
GFI	0.908
Hoelter's critical N (α = .05)	154.927
Hoelter's critical N (α = .01)	172.746

Residual variances details are presented in Table 16 that follows.

***Table 16:** Residual variances for speeding – Greek car drivers – experiment Phase 2*

Variable	Estimate	Std. Error	z-value	p
Time indicator	0.951	0.005	176.006	< .001
Duration	0.667	0.016	42.411	< .001
Distance	0.997	0.005	191.252	< .001
Age	0.629	0.004	151.007	< .001
Gender	0.540	0.004	130.780	< .001
Fuel type	0.995	0.005	194.984	< .001
Vehicle age	0.685	0.004	161.191	< .001
Gearbox	0.569	0.004	137.849	< .001
Harsh breaking	0.999	0.008	129.155	< .001
Harsh acceleration	0.995	0.008	129.341	< .001
Speeding level 0	21.018	8.341	2.520	0.012
Speeding level 1	1.038	0.017	61.946	< .001
Speeding level 2	0.957	0.006	160.887	< .001

The results for phase 3 are shown Figure 10 below.

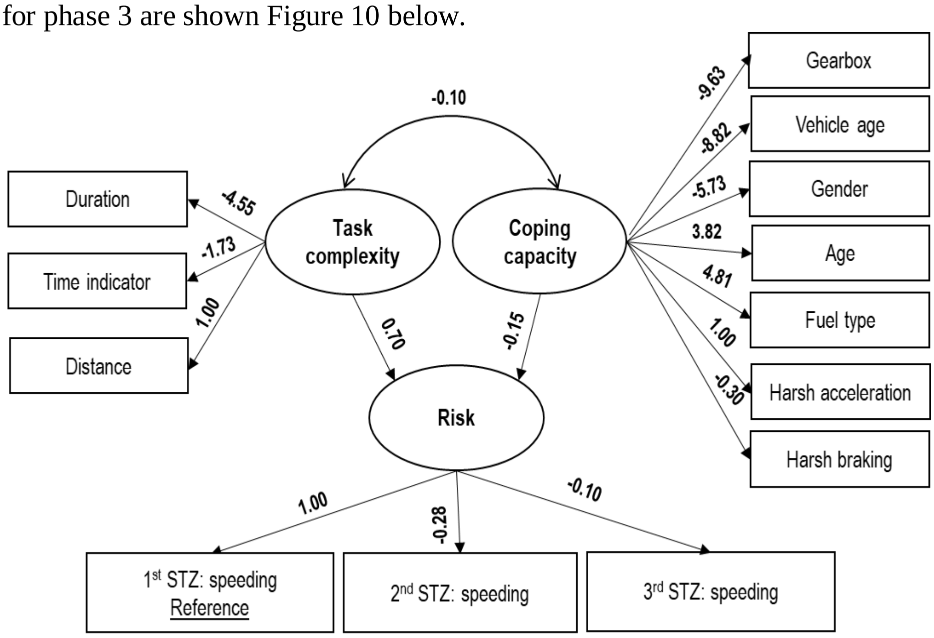

***Figure 10:** Results of SEM on risk (speeding STZ) – Greek car drivers – experiment Phase 3*

The Comparative Fit Index (CFI) of the model is equal 0.809, TLI is 0.759 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.111. Table 17 summarizes the model fit of SEM applied for speeding.

***Table 17:** Model Fit Summary for speeding – Greek car drivers – experiment Phase 3*

Model Fit Summary	
AIC	$4.326\times10^{+6}$
BIC	$4.326\times10^{+6}$
CFI	0.809
TLI	0.759
RMSEA	0.111
GFI	0.872
Hoelter's critical N (α = .05)	107.037
Hoelter's critical N (α = .01)	119.311

Residual variances details are presented in Table 18 that follows.

***Table 18:** Residual variances for speeding – Greek car drivers – experiment Phase 3*

Variable	Estimate	Std. Error	z-value	p
Distance	0.952	0.004	268.224	< .001
Duration	0.058	0.007	8.939	< .001
Time indicator	0.863	0.003	267.069	< .001
Harsh acceleration	0.995	0.006	168.036	< .001
Age	0.881	0.003	274.527	< .001
Gender	0.731	0.003	263.853	< .001
Fuel type	0.811	0.003	270.086	< .001
Vehicle age	0.363	0.002	188.467	< .001
Gearbox	0.240	0.002	129.755	< .001
Harsh breaking	1.000	0.006	167.717	< .001
Speeding level 0	-2.192	0.073	-30.049	< .001
Speeding level 1	0.758	0.006	120.858	< .001
Speeding level 2	0.925	0.004	219.243	< .001

7. Conclusions

The current research aims to examine the impact of task complexity and coping capacity on risk. To fulfil this objective, a naturalistic driving experiment was carried out and data from on road trials in Greece was collected representing car drivers, included four consecutive phases:

- Phase 1: baseline measurement

- Phase 2: real-time intervention
- Phase 3: real-time intervention and post-trip feedback
- Phase 4: real-time intervention and post-trip feedback and gamification

An integrated model per each phase was applied in order to gain an in-depth understanding of inter-relationship with risk. Questionnaire data were also collected providing useful information about the participants.

Results indicated that in phase 1, task complexity and coping capacity were inter-related with a positive correlation, which implies that drivers' coping capacity increases as the complexity of driving task increases. On the other hand, in phase 3, task complexity and coping capacity were negatively correlated. The effect of task complexity was generally greater than the one of coping capacity, whereas the peak of the contributions from task complexity and coping capacity was observed in phase 3.

The measurement of task complexity and its correlation with risk posed a challenge due to the limited number of variables that could be collected and utilized, leading to the use of proxies. For instance, the weather conditions, lighting conditions or night-time driving were not available and thus; these variables were not included in the analysis.

Overall, collection of the intended variables proved more difficult than anticipated. Future research could take into consideration the aforementioned challenges, and through adequate planning, accommodate the extensive requirements of such an endeavour. Incorporating information on factors like road configuration, traffic density, and other relevant metrics would be very useful in order to establish the complexity of the driving task and its association with risk.

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