D6.3 An integrated model of driver-vehicle-environment interaction and risk

Interview with George Yannis

The ultimate goal of this deliverable (D6.3) was to identify the impact that the "battle" between task complexity and coping capacity has on the risk of a crash. This time we talked with George Yannis, one of the co-authors of D6.3.

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Hello George, how are you? Time to take a closer look at D6.3. But before we dive into the results, I would first like you to clarify a couple of things for me.

GEORGE: *"I'm doing very well, thank you. And sure, fire away!"*

In this deliverable, but also in D6.1 an D6.2, numerous types of variables and models are mentioned. Can you explain them in an easy-to-understand way? And let's start with the variables. I came across several types: there were dependent and independent variables, discrete and continuous variables and latent variables. But what is the difference between all of those types?

GEORGE: *"Let's start with the independent versus the dependent variables. An <u>independent variable</u>, sometimes also called experimental or predictor variable, is a variable that is being manipulated in an experiment in order to observe the effect on a dependent variable. The <u>dependent variable</u>, sometimes also called outcome variable (e.g. test score), is simply that: a variable that is dependent on one or more independent variables (e.g. intelligence, time studied).*

Secondly, the discrete versus the continuous variables. A <u>discrete variable</u> is a variable that you can count (e.g. number of votes for a politician). A <u>continuous variable</u> is a variable that can take on any value within a range. It is a variable that you measure (e.g. a person's weight).

And then there were the latent variables. <u>Latent variables</u> are unobservable. They can only be inferred indirectly through a mathematical model from other observable variables that can be directly observed or measured (e.g. risk is a latent variable, inferred by taking into account observable variables such as: number of speeding events, tailgating events…)."

Next are the models. In this deliverable you talk about six different modelling techniques (see Figure 1). Some of them, I even find difficult to pronounce, let along understand. But maybe you can help with that?

GEORGE: *"I will do my best. I actually expected that you were going to ask me about this, because if you are not familiar with statistics, I can imagine it all sounds a bit complex. So, I will try to tackle them one by one."*

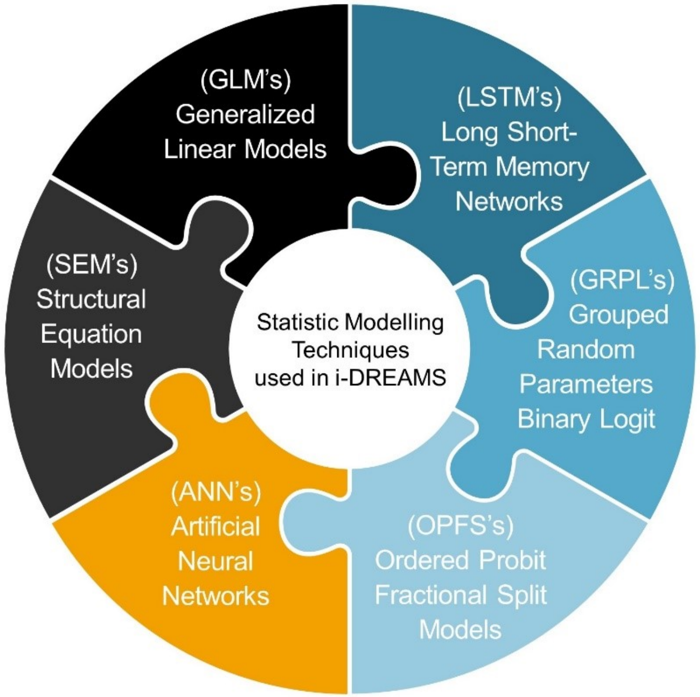

Figure 1: Statistic modelling techniques used in i-DREAMS

You may start with the Generalized Linear Models (GLM's)

GEORGE: *"GLM's unify various other statistical models, such as linear regression, logistic regression and Poisson regression. A <u>linear regression</u> is a technique to model the relationship between dependent and independent variables, for you to be able to make predictions. For example, if you know how many speeding events were registered for a driver in the past 500 kilometres driven on highways, you can use linear regression to predict how many events will be registered in the next 500 kilometres that he/she will drive on highways. <u>Logistic regression</u> is a technique to predict a dependent variable, with a binary outcome like yes or no, by analysing the relationship between one or more independent variables. The technique can be used for example to predict if a young novice driver will pass or fail his/her driving license exam. And <u>Poisson regression</u> is a technique to model events where the dependent variables are counts, e.g. number of events registered per trip, given one or more independent variables like weather conditions."*

OK, thank you! Then the Structural Equation Models (SEM's)

George: *"SEM's are a set of statistical techniques, used to identify the relationships between observed (e.g. number of speeding and tailgating events) and latent or unobserved variables such as crash risk. SEM's have two components. The <u>measurement component</u> determines how well observable variables can measure the latent variables and what the related measurement errors are. The <u>structural component</u> explores how the variables are interrelated, allowing for both direct and indirect relationships to be modelled. In this sense, SEM's differ from ordinary regression models, where the relationships between variables are always direct."*

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That is also clear, kind of (laughs). Then the techniques for real-time modelling. Let us begin with the Artificial Neural Networks (ANN).

GEORGE: *"An Artificial Neural Network (ANN) consists of an interconnected group of nodes, comparable to neurons in a brain. Each connection, like the synapses in a biological brain, can transmit a signal to another node. Connections between nodes are called edges. Nodes and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Nodes may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. An ANN is comprised of different layers of nodes: an input layer which contains values of the explanatory variables, hidden layers add up the weights of the explanatory variables and calculate the complex association patterns, and an output layer contains the output values, which are the result of the values of the various hidden nodes. Neural networks rely on training data to learn and improve their accuracy over time."*

Ok, I will remember that one as an artificial brain. Next on the list are the Long Short-Term Memory (LSTM) Networks.

GEORGE: *"LSTM Networks are also neural networks, but they have feedback connections, unlike the standard neural networks. They effectively store and access long-term dependencies using a special type of memory cell and gates. Cells remember values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cells. Input gates decide what new information is added and how to update the cell state. Forget gates decide what information is kept or removed from the cell state. Output gates decide which information is produced as an output."*

Cristal clear! Moving on to the post-trip modelling techniques. First, we have the Grouped Random Parameters Binary Logit (GRPL) Models.

GEORGE: *"To explain or predict a choice from a set of two or more alternatives, Discrete Choice Models are often used. The Binary Logit aspect refers to the dependent variable having a binary nature. For example: Will person X chose to travel by car or train to work? The dependent variables are car (binary value: yes/no) or train (binary value: yes/no). The independent variables: travel time, travel cost … An important disadvantage of Discrete Choice Models is that they don't take into account that the effects of explanatory variables may very across individuals. Therefore, in D6.3 GRPL models were used. They do the same as the simple binary logit models, but they also address that limitation because they do take the heterogeneity of the population into account."*

Then lastly, the Ordered Probit Fractional Split (OPFS) Models.

GEORGE: *"Ordered Probit models are used for situations where there are more than two outcomes of an ordinal dependent variable. This is a variable for which the potential values have a natural ordering, e.g. STZ level 1, STZ level 2, STZ level 3. The Fractional Split aspect refers to the fact that the outcome is fractional and not binary. This implies that when modelling speeding behaviour for example over a period of time (1 minute), multiple speeding categories may occur in that one minute of time. The driver's speeding behaviour can be in STZ level 1 for 35% of that time window, in STZ level 2 for 45% of that time window and in STZ level 3 for 20% of that time window."*

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It is still somewhat confusing to me, although I have to admit that I am slowly starting to understand these technical things a bit better.

GEORGE: *"Great! That is music to my ears."*

Let me proceed with the results of the analysis. If I understood correctly, chapter 4 synthesised what was also discussed in D6.1 and D6.2?

GEORGE: *"That is correct! We elaborated on the impact of task complexity factors (scope of D6.1) and coping capacity factors – vehicle state and operator state – on risk (scope of D6.2). We determined which factors had the most impact on risk and highlighted the main findings in the different countries and for the different modes."*

Could you briefly explain those findings again?

GEORGE: *"With pleasure! The analyses demonstrated that in Belgium task complexity and coping capacity were positively correlated in the majority of the models, which means that with higher task complexity comes higher coping capacity, a non-intuitive result. Task complexity was found to have greater loadings on risk, but that effect dropped when observing trips from phase 1 to phase 4 (see Figure 2 for an overview of all the phases) of the experiment. Furthermore, in many of the developed models the loadings revealed a spike in their values during phase 3 of the experiment and a small drop in phase 4, which points to the fact that the combination of real-time and post-trip feedback significantly influenced the relationship between task complexity, coping capacity and risk, whereas gamification in some cases might have confused drivers.*

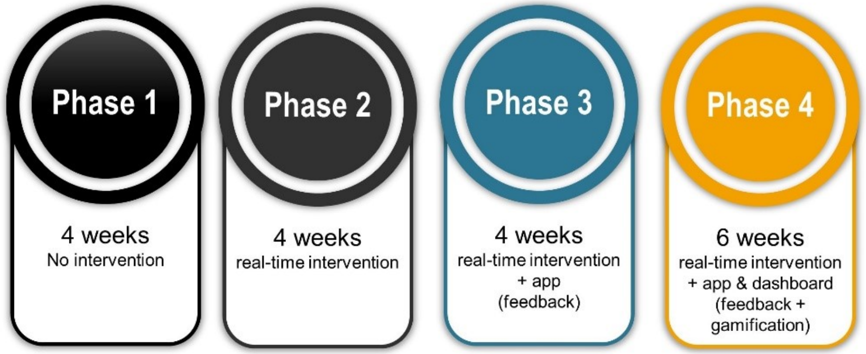

Figure 2: Four phases of the experiments

In the UK, loadings from the SEM models demonstrate that coping capacity and task complexity were positively correlated in phase 1 and 3, but had no significant relationship in phase 2 and phase 4. Like in Belgium, task complexity had a stronger impact on risk, with phase 3 showing the greatest effect.

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

Lastly, in Greece, in the majority of the models, task complexity and coping capacity were again negatively correlated with risk. The effect of coping capacity was generally greater than the one of task complexity, in contradiction with the rest of the countries, whereas the peak of the contributions from task complexity and coping capacity was observed in phase 3.

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Looking at the observed risk factors, it was demonstrated that for the speeding and the headway models, the correlation of task complexity and coping capacity with risk was positive, with the main exceptions being observed in phases 2 and 3 in Greece, Germany and Belgium. For harsh accelerations in Belgian trucks, the correlation of coping capacity and task complexity with risk was in general positive along the same magnitude for all phases. The detailed results are actually visualized in Table 1."

Table 1: Correlation effect of task complexity and coping capacity on risk per indicator / phase / country / transport mode

Country (transport mode)	**Risk (indicator)**	**Phase 1**		**Phase 2**		**Phase 3**		**Phase 4**	
		TC	**CC**	**TC**	**CC**	**TC**	**CC**	**TC**	**CC**
BE (cars)	speeding	-	+	-	+	-	+	+	+
	headway	-	+	-	+	-	-	-	+
BE (trucks)	speeding	-	-	-	-	-	-	-	-
	harsh acceleration	+	-	+	-	+	-	+	-
	headway	-	-	-	-	-	-	+	-
UK (cars)	headway	-	-	+	-	-	-	-	-
DE (cars)	speeding	+	-	+	-	+	-	+	+
GR (cars)	speeding	+	-	+	-	+	-	+	-
	headway	+	-	+	-	+	-	+	-

*TC refers to Task Complexity and CC refers to Coping Capacity

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Could you also shine a light on the modelling results described in chapter 5?

GEORGE: *“OK, I will try. In chapter 5 we performed real-time (ANN and LSTM) and post-trip (GRPL and OPFS) analyses to examine the impact of vehicle, operator and context characteristics on risk under different conditions. We also made comparisons between countries and transport modes. Via ANN we investigated if real-time predictions of the STZ and its three levels is possible. The answer is yes! Via LSTM networks we tried to predict in real-time ‘dangerous speeding levels’ and ‘dangerous levels of headway’. These results were not significant.*

Via GRPL models we investigated the occurrence of near-misses in the 4 phases of the experiment under various conditions such as night-time driving, years of holding a driving license … (= explanatory factors). The overall conclusion was that near-misses appeared to be random events whose explanatory factors do not differentiate between different phases of the experiment.

For each phase of the experiment an OPFS model was fitted to investigate the propensity of speeding taking into account specific variables related to the environment (night-time), driver’s characteristics (e.g. gender, age...) and personality characteristics (e.g. perceived competence, norms and values). Although there is indication that the introduction of interventions reduces the role of the environmental variable (night-time) and the drivers’ general characteristics, and strengthens the role of personality characteristics, the small samples do not allow for a final conclusion.”

To conclude this interview … If you could summarize the findings of all the analyses that were performed in this deliverable in maximum four bullet points, what would they be?

GEORGE: *“I would say that we were able to better understand the relationship between task complexity, coping capacity and risk and that our main findings are the following:*

- *For the majority of the risk factors investigated it was found that higher task complexity levels lead to higher coping capacity with the drivers. This means that drivers, when faced with difficult conditions, tend to regulate well their capacity to apprehend potential difficulties, while driving.*
- *When looking into the relationship between the interaction of task complexity and coping capacity and its effect on risk, in Belgium and Germany it was shown that the influence of task complexity on risk was greater than the effect of coping capacity, while in Greece, coping capacity had a greater impact on risk. Mixed results were observed in the UK.*
- *The comparison of models fitted on data from the different phases of the experiments, validated that in the majority of the countries the interventions had a positive influence on risk compensation, increasing the coping capacity of the drivers and reducing the risk of dangerous driving behaviour.*

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Deliverable 6.3 is part of WP6:
Analysis of risk factors

- *Predictive real-time analyses demonstrated that it is possible to predict the level of STZ with an up to 95% accuracy with only few false alarms, while post-trip explanatory studied showcased the capacity of state-of-the-art econometric models to shed light on the complex relationship of risk with the interdependence of task complexity and coping capacity."*

Thank you George!
Edith Donders
i-DREAMS DisCom manager

i-DREAMER in the spotlight

GEORGE YANNIS

Graduated as *Civil Engineer in 1987*

Employed at *National Technical University of Athens since 1993*

Passionate about *road safety and marathons*

Tasks in i-DREAMS: *Leads work packages on the analysis of risk factors and the evaluation of safety interventions & Coordinates the NTUA team contributions*

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