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Quantifying the impact of driver, vehicle and environment on crash risk using big data

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Introduction

- Several crucial indicators have a **significant impact on road safety**
- Factors such as **speeding**, distracted or aggressive driving, and non-compliance with traffic regulations can increase the crash risk
- The condition and **safety features of vehicles** also play a critical role in averting crashes and reducing the likelihood of serious
- **Environmental conditions** such as adverse weather, poor visibility, and uneven road surfaces can increase the likelihood of crashes

Objectives

- Examination of the impact of **driver, vehicle and environment** on crash risk
- Identification of the most critical indicators of risk from both the **task complexity and the coping capacity** (vehicle and operator state) side
- A **naturalistic driving experiment** was conducted and a large database was collected and analysed, consisting of:
  - ✓ 135 drivers aged 20-65
  - ✓ 4 months
  - ✓ 31,954 trips

The Experiment

The experimental design of the on-road study has been subdivided **into four consecutive phases**:

- **Phase 1** of the field trials refers to a reference period after the installation of the system inside the vehicle in order to monitor driving behaviour without interventions
- **Phase 2** of the field trials refers to a monitoring period during which only in-vehicle real-time warnings were provided using Advanced Driver Assistance Systems
- In **phase 3**, feedback via the smartphone app is combined with in-vehicle warnings
- In **phase 4**, gamification features are added to the app, with additional support of a web-dashboard

Phase 1 (Baseline)
- **Intervention**: NO
- **Description**: a reference period to monitor driving behaviour without interventions
- **Duration**: 4 weeks

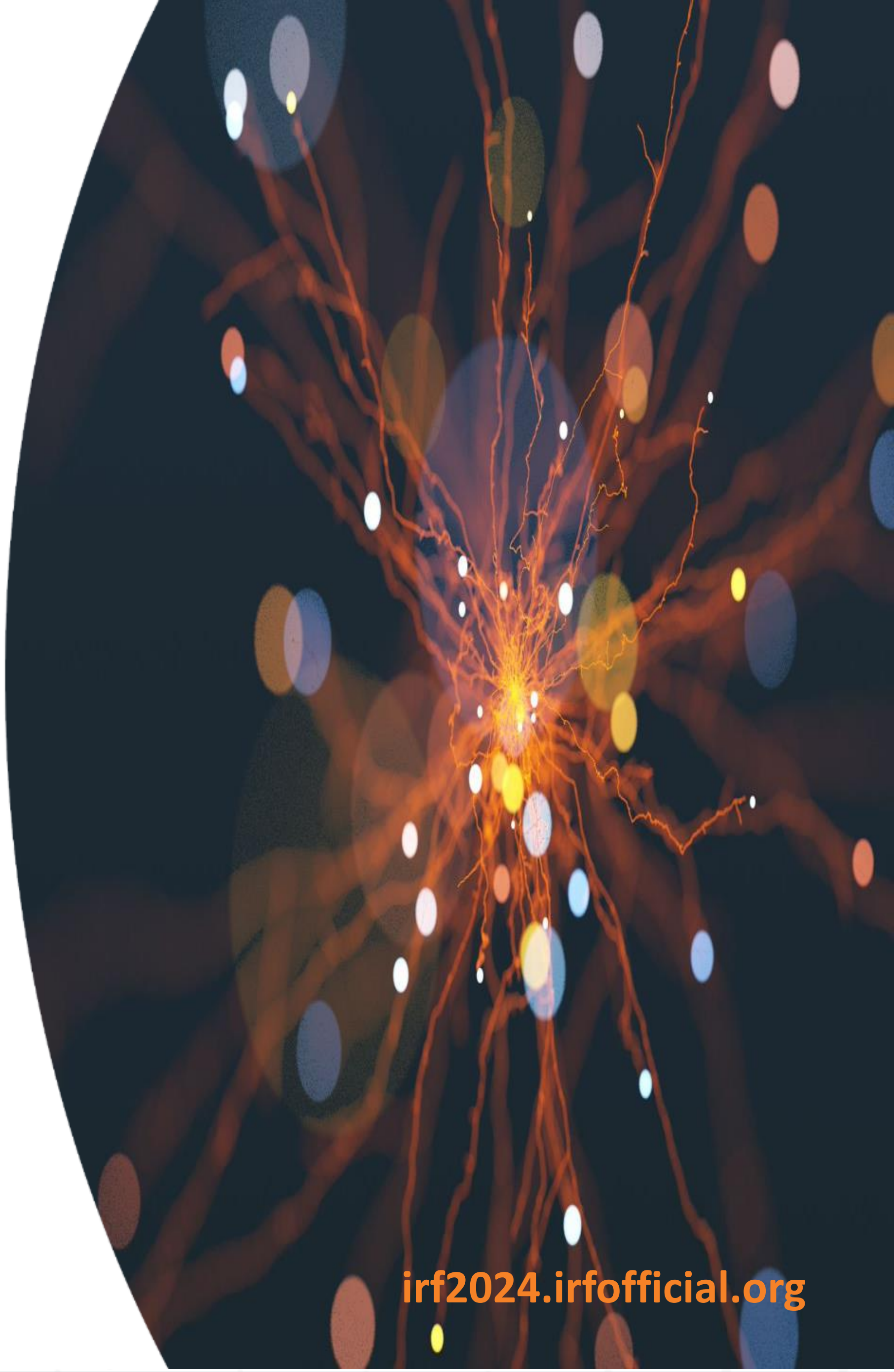
Phase 2
- **Intervention**: Real-time
- **Description**: a monitoring period during which only in vehicle real-time warnings provided using adaptive ADAS
- **Duration**: 4 weeks

Phase 3
- **Intervention**: Real-time + Post-trip
- **Description**: a monitoring period during which in addition to real-time in vehicle warnings, drivers received feedback on their driving performance through the app
- **Duration**: 4 weeks

Phase 4
- **Intervention**: Real-time + Post-trip + Gamification
- **Description**: a monitoring period during which in vehicle real-time interventions were active along with feedback but at the same time gamification elements were also active
- **Duration**: 6 weeks

Methodology

- **Generalized Linear Models** (GLMs) were developed and explanatory variables of risk and the most reliable indicators, such as time headway, distance travelled, speed, time of the day or weather conditions were assessed
- **Structural Equation Models** (SEMs) were used to explore how the model variables were inter-related, allowing for both direct and indirect relationships to be modelled



Data Overview

- **Task complexity** relates to the current status of the real world context in which a vehicle is being operated:
  - ✓ road layout (i.e. highway, rural, urban)
  - ✓ time and location
  - ✓ traffic volumes (i.e. high, medium, low)
  - ✓ weather conditions
- **Coping capacity** is dependent upon two underlying factors and it consists of several aspects:
  - ✓ vehicle state (e.g. technical specifications, actuators & admitted actions, current status)
  - ✓ driver state (e.g. mental state, sociodemographic profile)

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

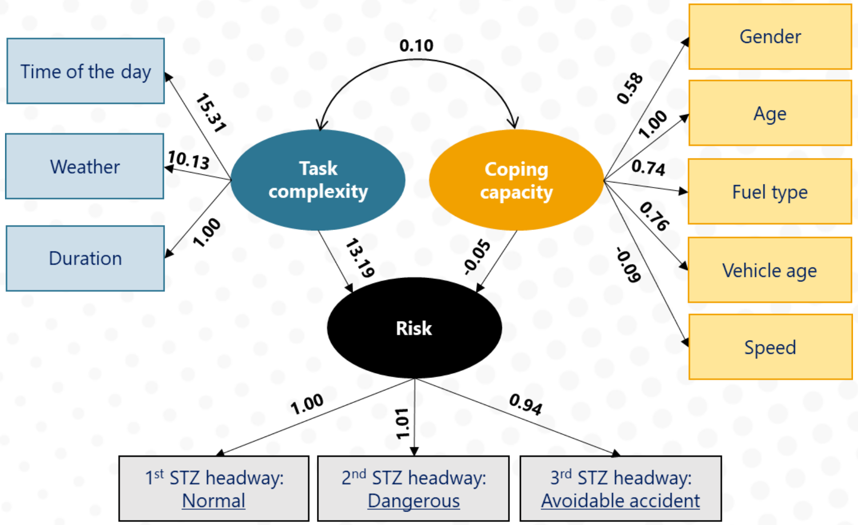
Results - Generalized Linear Models

- Time of the day was **negatively correlated with headway**, which means that drivers tend to keep safer distances from the vehicle in front of them during the night
- The wipers variable was found to **have a positive correlation with headway**, indicating that there are more headway events during adverse weather conditions
- **Vehicle age had a positive relationship with headway**, indicating that as the vehicle age increases, the likelihood of headway events also increases
- Indicators of **coping capacity – driver state**, such as duration, harsh acceleration, harsh braking and average speed had a positive impact on headway

Variables	Estimate	Std. Error	z-value	Pr(|z|)	VIF
(Intercept)	-0.340	0.002	-151.275	< .001	-
Time indicator	-4.633×10-4	1.467×10-4	-3.158	0.002	1.001
Weather	0.060	0.007	9.026	< .001	1.006
Fuel type - Diesel	-3.430×10-5	1.897×10-6	-18.084	< .001	4.889
Vehicle age	3.318×10-5	1.640×10-6	20.236	< .001	5.995
Gearbox - Automatic	-7.127×10-6	2.303×10-6	-3.095	0.002	3.289
Duration	9.232×10-7	2.569×10-7	3.593	< .001	1.058
Harsh braking	5.703×10-5	1.753×10-6	32.533	< .001	3.397
Harsh acceleration	4.587×10-5	1.819×10-6	25.216	< .001	3.405
Average speed	2.018×10-5	7.686×10-7	26.254	< .001	1.111
Gender - Female	-1.595×10-5	1.818×10-6	-8.775	< .001	1.495
Age	3.891×10-5	1.913×10-6	20.336	< .001	5.342
Summary statistics					
AIC	1.394×10+6				
BIC	1.165×10+6				
Degrees of freedom	822163				

Results - Structural Equation Models (1/2)

- The latent variable risk is measured by means of the **STZ levels for headway** (level 1 refers to 'normal driving' used as the reference case, level 2 refers to 'dangerous driving' while level 3 refers to 'avoidable accident driving')
- Task complexity and coping capacity **are inter-related with a positive correlation**, implying that drivers coping capacity increases as the complexity of driving task increases
- **Task complexity and risk shows a positive coefficient**, which means that increased task complexity relates to increased risk
- 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

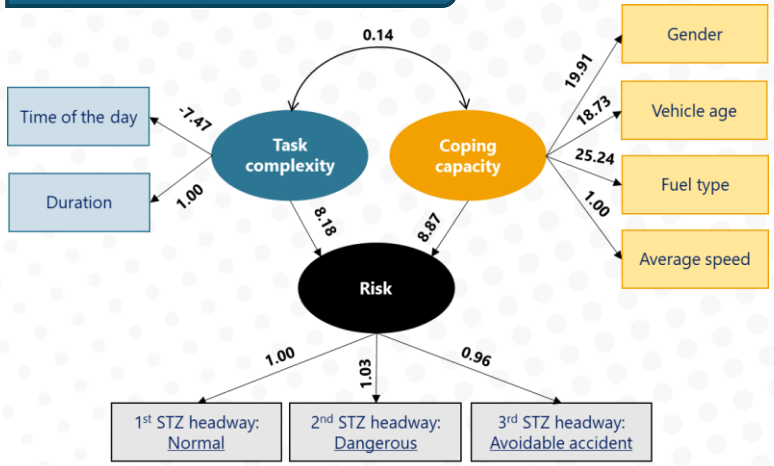


Model Fit measures	Overall
CFI	0.945
TLI	0.927
RMSEA	0.106
GFI	0.921
Hoelter's critical N (α = .05)	224.059
Hoelter's critical N (α = .01)	241.364
AIC	2.043×10+7
BIC	2.043×10+7

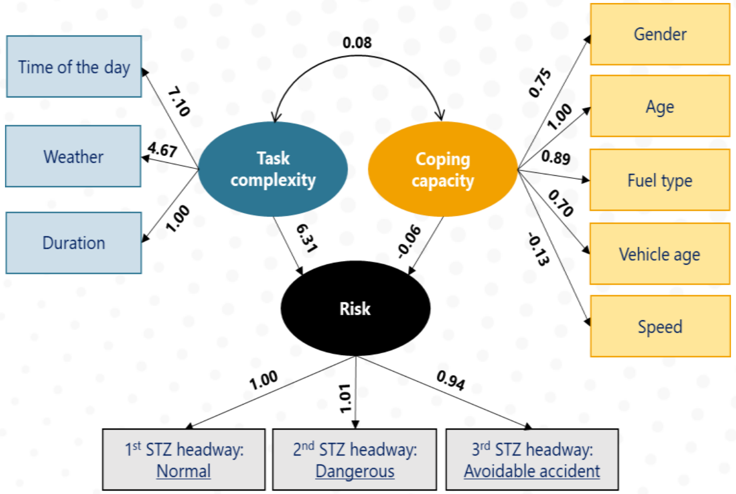
Results - Structural Equation Models (2/2)

- Higher task complexity was associated with an **increased crash risk** in all phases, as drivers could probably become overwhelmed by the demands of complex tasks
- The loadings of the observed proportions of the STZ of headway **are not consistent among the different phases**, as slight differences were observed among phases
- **Coping capacity and risk** found to have a positive relationship in phases 1 and 2 of the experiment and a negative relationship in phases 3 and 4
- 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

Experiment Phase 1



Experiment Phase 4



Discussion

- Driving during night-time or in adverse weather conditions, such as rain or fog can affect the **challenges posed by complex tasks**, further increasing the likelihood of crashes
- Overall, drivers with higher coping capacity are better equipped to **handle complex and challenging driving situations**, as they can manage stress, make quicker and more accurate decisions and maintain better control over their vehicles, all of which contribute to safer driving
- Models fitted on data from different phases of the on-road experiment validated that both real-time and post-trip interventions **had a positive influence on risk compensation**, increasing drivers' coping capacity and reducing dangerous driving behaviour

Conclusions

- By integrating task complexity, coping capacity, and risk, it is possible to improve the behaviour and safety of all travellers through **unobtrusive and seamless** behaviour monitoring

- Providing **feedback and training** to travellers can enhance travel behaviour, encourage shifts to safer and eco-friendly modes, and ultimately reduce risk

- Authorities can utilize **population-level data systems** to plan mobility and safety interventions, set up road user incentives, optimize enforcement, and foster community engagement in safe travelling

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