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Research Article

Unpacking the relationship between task complexity and driving risk: Insights from a UK on-road trial

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ABSTRACT

This study investigates the intricate relationship between task complexity and driving risk through a comprehensive four-phase on-road trial conducted in the UK. Employing Structural Equation Modelling (SEM), the research illuminates the factors influencing task complexity and its association with risk, treating both as latent concepts—unobservable variables in the study. The findings reveal a notable positive correlation between task complexity and risk, particularly concerning the headway indicator. In essence, the study demonstrates that an escalation in task complexity corresponds to an increased level of risk.

Throughout the four SEM analyses performed across two waves of on-road trials, the time spent in each safety tolerance zone level for headway measurements emerges as a key indicator of the latent construct of risk in all phases. Notably, the variables constituting the latent concept of task complexity—those proven statistically significant—show slight variations across phases. Variables consistently significant across all phases include the number of right Lane Departure Warnings (LDWs) per 30 s and the day of the week.

The models reveal the feasibility of quantifying the risk-task complexity relationship in real-world driving settings. This study provides insights to inform efforts to mitigate risk exposure through design and training interventions, targeting the most predictive factors linked to task complexity. Driver demographics did not emerge as statistically significant, emphasising the need for a holistic approach to improve road safety.

1. Introduction

Task complexity has been recognised as one of the most important determinants of human behaviour and task performance [1]. As Hackman [2] argued, “tasks play an important role in much research on human behaviour, and differences in tasks and task characteristics have been shown to mediate differences in individual and social behaviour.” Task complexity lacks a unified definition and consistent measurement methods, resulting in varying interpretations and assessments across different contexts [3]. High complexity tasks are usually dynamic and require greater demands on skills, knowledge, cognitive abilities, memory capacities and efforts.

Driving is a complex task that demands constant attention, cognitive processing, and precise motor skills. The complexity of the driving task is partly determined by the demands of the road environment, traffic restrictions, weather conditions and time of the day or location [4]. However, driving task complexity is also associated with driver performance, such as harsh events, driving speeds, or following distances. The complexity of a driving situation can be further influenced by various factors including infrastructure and traffic characteristics; for instance, an increase in traffic density or traffic signs can increase a driver’s workload and take-over times [5–9]. Driving task complexity is to be understood as a multi-dimensional concept, entailing a variety of endogenous and exogenous factors, and relates to the current status of the real-world context in which a vehicle is being operated [10]. More in detail, relevant factors for monitoring context are road layout, time and location, surrounding traffic, and weather. Task demand identifies factors which influence the level of individual effort in a given traffic scenario.

Technological innovations, such as adaptive cruise control (ACC), navigation systems, smart phones, in-vehicle and roadside traffic information systems, and automatic lane control (ALC) have shifted drivers from purely being a controller of the driving task towards also being a manager of information while driving. As advancements in automotive technology and connectivity continue to reshape the driving environment, understanding the intricate interplay between task

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complexity and driving risk becomes essential for ensuring road safety.

The concept of task complexity relates to Fuller's Task-Capability Interface model (TCI) [11–13]. Fuller states that safe driving is determined by two interacting elements: the driver's capability and driving demands. If these are in balance, the risk is low, if not, the risk increases. This paper focuses on elements that increase the demands of the driving task and therefore make it more complex and aims to shed light on the dynamic relationship between task complexity and driving risk through insights derived from an on-road trial of car drivers conducted in the United Kingdom. The trial collected real-world data on driver behaviour, and structural equation models were then employed to explore the latent concept of task complexity and its relationship with driving risk. Key findings demonstrate that increased task complexity is associated with increased driving risk. By exploring the multifaceted aspects of task complexity and their implications on driving behaviour, this research aims to provide valuable contributions in crafting evidence-based interventions to mitigate driving risk and enhance overall road safety in an increasingly complex driving landscape.

2. Literature review

Driving is influenced by a wide range of factors, each contributing to the complexity of the task and hence influencing crash risk. This literature review explores the effects of road layout, traffic, weather, and time of the day on driving complexity and risk. It also highlights studies that investigate the relationship between driving task complexity and risk, including the role of environmental and secondary task factors. Furthermore, the review considers how Structural Equation Modelling (SEM) has been applied to study driving behaviours, particularly within the context of task complexity and coping capacity.

2.1. Road layout

Regarding road layout, researchers have noted that an increased number of lanes corresponds to heightened task demands [14,15]. Additionally, both narrow lanes [16,17] and wider lanes experiencing high traffic volumes [15] intensify task demands, consequently elevating the risk of crashes, accidents, injuries, or fatalities. Moreover, it has been discovered that longer deceleration lanes [18] and challenging road features like spirals, highway curves, or geometric designs [19] contribute to more difficult driving conditions, thereby increasing the likelihood and frequency of crashes. Similarly, minor right-turn lanes, main and secondary roads, or motorways amplify task demands and the risk of crash occurrences [20,21]. Valent et al. [22] found that driving in an urban area results in higher task demands and an increased anxiety regarding the risk of fatal and non-fatal injuries.

In addition to these factors, research has also shown that drivers may adapt their behaviour to changes in task complexity due to secondary task demands and road environment factors. For instance, a study by Onate-Vega et al. [23] found that drivers are likely to overcorrect their position in the vehicle lane in the presence of pedestrians and oncoming traffic. The effect of road geometry on driver behaviour was found to be greater than the effect of mobile phone distraction. Curved roads and hills were found to influence preferred speeds and lateral position the most.

2.2. Traffic

Studies have shown that the volume of traffic through-traffic per lane on minor roads has an impact on task demand, with Guo et al. [24] reporting a decrease in the latter. However, all the studies agree that congestion is associated with heightened driving difficulty and an increased likelihood of crashes. Specifically, Shi et al. [25] found that congestion has a detrimental effect on crash frequency, particularly during peak hours. Additionally, it was discovered that both congestion and, to a lesser extent, transition, contribute to increased driving complexity, thus elevating the risk of crashes [26]. Golob et al. [27] have indicated that when the entire road is congested, the task demand increases as crashes are more likely to occur. Finally, Wang et al. [28] demonstrated that a 1 % increase in traffic delay per kilometre, resulting in very slow-moving vehicles, led to approximately a 0.1 % increase in KSI crashes (crashes resulting in killed or seriously injured individuals).

2.3. Weather

Weather conditions have a significant impact on task demand during driving. For instance, the intensity or duration of rain [29] and the height of rainfall [31] increase the complexity of driving. Martensen et al. [32] investigated frost's effect and found a remarkable 71 % increase in task demand on motorways. Rainfall has been linked to a higher accident risk, particularly evident in the increased number of victims among car occupants during rainy conditions. Notably, motorcyclists face even more pronounced risk factors related to rain, such as impaired vision, reduced visibility, and decreased friction, compared to car users. On the other hand, snow was associated with a decrease in the total number of injuries or fatal crashes, as well as two-wheeler and car collisions, while its impact was not significant in other cases. Fog has been shown to have a negative impact on task demand, as revealed in studies by Abdel-Aty et al. [33] and Sabir [34], indicating an increased likelihood of injury accidents under foggy conditions. Overall, weather conditions like precipitation, sun, wind, frost, and snow days were found to increase driving complexity [32].

2.4. Time of the day

Regarding the impact of time on driving, research has highlighted that darkness, the absence of street lighting, and twilight significantly influence task difficulty for drivers [35]. Darkness, in particular, has been associated with a 30 % increase in task demand and crash risk in urban areas, a 50 % increase in rural areas, and a 40 % increase in both rural and urban areas [36]. In terms of the time of day, higher task complexity and driving risk were observed during the early morning hours from 05:00 to 06:00 and in the evening hours from 17:00 to 19:00 for both national and regional roads [37].

2.5. Driving task complexity and risk

Many studies have examined the relationship between driving task complexity and risk. Drivers optimise workload by adjusting their behaviour [12]. Fuller [38] and Kinnear et al. [39] both found a link between subjective feeling of task difficulty in reaction to speed and feelings of risk by showing participants video clips. Lewis-Evans and Rothengatter [40] used a driving simulator to test this more objectively and found that drivers prefer to operate (choose speeds) where their subjective feelings of risk and difficulty is low. Environmental factors such as narrow lanes, low visibility, roadwork zones and road signs can make the driving task more complex and increase risk (e.g. [41,42]). The relationship between the complexity of the driving task and risk has also been studied in relation to secondary tasks (e.g. [23,43]). Many of the aforementioned studies use experimental methods such as driving simulators. Studies examining the relationship between task complexity and risk using real-world naturalistic data are lacking and this paper seeks to address this research gap.

2.6. SEM in driving behaviour studies

Structural equation modelling has been previously used to examine driving behaviours and their underlying factors. Studies often employ SEM to explore latent variables like situation awareness (SA), risk perception, and workload, which are difficult to measure directly. For instance, Yang et al. [44] demonstrated how SA, influenced by factors such as road characteristics, driver state, and distractions, impacts driving decision-making and risk. Other studies have utilised SEM to investigate risky driving behaviours through frameworks like behaviour change models [45] and self-regulation strategies. These methods, often supported by survey or simulator data, provide comprehensive insights into how drivers adapt their behaviours to perceived task complexity and environmental challenges [43,46]. I-DREAMS was the first project to use SEM to examine the relationship between task complexity and coping capacity within the context of Fuller's TCI model ([11–13]) and this paper focuses on the task complexity elements of the UK data.

This literature review highlights the existing research on the relationship between driving task complexity and risk, focusing on road layout, traffic volume, congestion levels, and weather conditions influence on task demands. While these factors are recognised as critical, the latent nature of task complexity and its intricate relationship with driving risk remain underexplored. This study addresses this gap by utilising advanced statistical methods, such as SEM, applied to real-world data. By uncovering these underlying mechanisms, this research aims to inform the development of targeted and more effective interventions to mitigate risks and enhance road safety.

3. Methodology and data preparation

3.1. UK on-road trial

54 private car drivers were recruited to an instrumented field operational trial as part of the H2020 European Commission supported project, i-DREAMS. The aim of i-DREAMS was to develop a system that through real-time warnings and post trip feedback, assists the driver in reducing risk within the concept of a "Safety Tolerance Zone (STZ)." The project defined three STZ levels: 1) normal driving phase (minimised risk); 2) danger phase (increased risk); 3) avoidable accident phase (highest risk, immediate action needs to be taken). The real-time warnings and post-trip feedback respectively aimed to "nudge" and "coach" the driver into maintaining safe driving behaviours, i.e., to return to and stay within the first level of the STZ.

Participants drove their own vehicles for the trial, which were equipped with the i-DREAMS system. The trial lasted for 18 weeks, split into four data collection phases:

- Phase 1: 4-weeks with no interventions (baseline monitoring period).
- Phase 2: 4-weeks with real-time warnings only (related to time headway including forward collision avoidance, vulnerable road user collision avoidance, lane departure, speeding, fatigue, handheld mobile phone use).
- Phase 3: 4-weeks with real-time warnings and post-trip app-based feedback (on all of the real-time measures plus vehicle control events, i.e., harsh acceleration, deceleration and steering).
- Phase 4: 6-weeks with real-time warnings, app-based post-trip feedback, plus app-based gamification features (group leaderboard rankings and individual driving goals).

Similar trials took place in other 3 European countries (Belgium, Germany and Portugal) in the framework of H2020 EU project i-DREAMS [47].

Participants were given a thorough briefing at the start of the trial to make sure they fully understood both the i-DREAMS in-vehicle system and smartphone app. Questionnaires were used at the beginning and end of the trial, to collect demographic information, as well as participants opinions on driver assistance systems and acceptance of the i-DREAMS system.

The three STZ levels were applied individually to each variable. For example, the driver could be in STZ level 2 for "speeding" and STZ level 1 for "headway" at the same time. Real-time warnings became more severe as drivers moved from level 2 to level 3, and the scores given in the post-trip feedback reflected the number of events triggered for each level. For practical reasons, drivers were recruited in two consecutive waves, resulting in data being collected between October 2021 and August 2022. Further details of the trial methods and results can be found in [48].

3.2. Data

The data used in this UK on-road trial were collected as part of a carefully designed study, detailed in the i-DREAMS project Deliverable 7.2 ([48]). Thresholds for the analysis were informed by an extensive literature review (in i-DREAMS Del3.2, [49]) and pilot testing. Key variables, such as speeding, were derived from CAN bus data, with speed limits cross-referenced using Mobileye and map data. While simulator trials were conducted to test fatigue thresholds, their findings are less central to this paper. The data validation process ensured the robustness of the results, as outlined in the project deliverables.

The fundamental challenge within this study is how explanatory variables (i.e., performance metrics and indicators of task complexity) are correlated with the dependent variable "risk" in order to predict the STZ level. There are three main types of variables which were used within i-DREAMS project: (1) discrete variables, such as fatigue (yes, no), time of the day (daytime, night-time driving) and STZ (normal phase, danger phase, avoidable accident phase), (2) continuous variables, such as speed and time headway, and finally, (3) latent variables, that are not observed directly by the analyst and therefore, 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 thus, observed indicators are needed to measure them. Risk is also conceived in i-DREAMS as a latent variable.

Explanatory variables of risk and the most reliable indicators of task complexity were assessed. More specifically, for risk the main factors that were explored to represent the latent construct were vehicle control events (e.g., harsh braking), speeding and headway behaviour, while for task complexity they were weather and lighting conditions, average speed, headway, month, day of the week, harsh accelerations, harsh braking, harsh cornering, distance travelled, duration, vehicle age, forward collision warnings, lane departure warnings (**LDW**s) or pedestrian collision warnings. Table 1 presents an overview of the variables collected within i-DREAMS that were included in the final model. The selection of the variables was based on their statistical significance in the model.

Due to the lack of weather information, the variable of "wipers in use" was utilised as a proxy. Demographic variables including age and gender were also considered for the model development. Due to the intended explanatory nature of the analysis, a post-trip approach was employed, where the collected data was aggregated and analysed after the trip has been completed. Latent variables analysis was applied to quantify the effects between latent and observable variables of task complexity and risk.

3.3. Structural equation models (SEMs)

Structural Equation Modelling (SEM) is widely used for modelling complex and multi-layered relationships between observed and unobserved variables. 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.

Table 1
Specification of the variables utilised in the model.

Source	Variable	Description	Range
i-Dreams STZ	iDreams_Headway_Map_level_-1	Real-time headway intervention level − 1 **level − 1** ≥ no vehicle detected (Normal Driving)	0 - intervention level unequal to −1 1 - intervention level equal to −1
	iDreams_Headway_Map_level_0	Real-time headway intervention level 0 **level 0** ≥ vehicle detected, but headway ≥ 2.5 s (Normal Driving)	0 - intervention level unequal to 0 1 - intervention level equal to 0
	iDreams_Headway_Map_level_1	Real-time headway intervention level 1 **level 1** ≥ vehicle detected, headway <2.5 s, but above warning threshold (Normal Driving)	0 - intervention level unequal to 1 1 - intervention level equal to 1
	iDreams_Headway_Map_level_2	Real-time headway intervention level 2 **level 2** ≥ first warning stage (Dangerous Driving)	0 - intervention level unequal to 2 1 - intervention level equal to 2
	iDreams_Headway_Map_level_3	Real-time headway intervention level 3 **level 3** ≥ second warning stage (Avoidable Accident)	0 - intervention level unequal to 3 1 - intervention level equal to 3
Mobileye	ME_Car_wipers	Wipers	0 - missing values False - Wipers are off, True - Wipers are on
	ME_Car_high_beam	High-beam	0 - missing values False - High-beam is off True - High-beam is on
	ME_LDW_Map_type_R_mean	Right lane departure warning	0 - missing values False - Right Lane departure warning is inactive True-Right Lane departure warning is active

The general formulation of SEM is as follows [50,51]:

$$\eta = \beta\eta + \gamma\xi + \varepsilon \tag{1}$$

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 [52]:

$$x = \Lambda_x\xi + \delta, \text{for the exogenous variables} \tag{2}$$

$$y = \Lambda_y\eta + \zeta, \text{for the endogenous variables} \tag{3}$$

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 Λ_x, Λ_y 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.

3.4. Model goodness-of-fit measures

In the context of model selection, model Goodness-of-Fit measures constitute an important part of any statistical model assessment. Several goodness-of-fit metrics are commonly used, including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the (standardised) Root Mean Square Error Approximation (RMSEA), the goodness-of-fit index (GFI), and Hoelter's index. 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 [53].

$$AIC = -2\,L(\theta) + 2q \tag{4}$$

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 -2 L(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.

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

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 [54]. 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_H^2 is the value of x^2 and df_H is degrees of freedom in the hypothesized model, and x_I^2 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 [54]. 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_H^2 is the value of x^2 and df_H is the degrees of freedom in the hypothesized model, and x_I^2 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 [55]. 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_H^2 represents the discrepancy between the observed and predicted covariance matrices for each element H, df_H represents the degrees of freedom in the hypothesized model and n is the sample size.

The Goodness of Fit Index (GFI) is a measure of fit between the hypothesized model and the observed covariance matrix. The adjusted goodness of fit index (AGFI) corrects the GFI, which is affected by the number of indicators of each latent variable [56]. 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's index is calculated to find if chi-square is insignificant or not. Hoelter's index involves calculating the critical value of the test statistic (e.g., t-value or F-value) at a predetermined significance level (alpha), and then identifying the sample size at which this critical value is equal to or greater than the maximum value of the test statistic that can be obtained for that sample size. This sample size is considered the minimum sample size required to achieve the desired level of statistical power. If Hoelter's index is more then 200, then the model is considered to be good fit with observed data (Hoelter>200). Values of less than 75 indicate very poor model fit. The Hoelter's index only makes sense to interpret if $N > 200$ and the chi square is statistically significant.

3.5. The theoretical model

In order to comprehensively explore the intricate relationship between risk and task complexity, a theoretical framework was essential. Given the data availability and existing literature, the theoretical model presented in Fig. 1 was developed to integrate latent constructs and factors that reflect the multifaceted nature of risk and driving task complexity.

The variables included in the theoretical model were selected based on their relevance to driving task complexity, as identified in the literature and within the framework of the project. Following Fuller's Task-Capability Interface (TCI) model, these variables were chosen for their potential to influence task demand and risk. Variables collected during data collection or as proxies for the model were aligned with the concept of the safety tolerance zone, ensuring the framework captured critical elements affecting driving task complexity and risk.

The initial SEM diagram illustrates the hypothesized structural relationships among the variables under investigation. Wipers can be an indication of weather conditions, most specifically, they can be indicative of rain presence during the trip, while high beams can indicate lighting conditions, for example, low visibility or darkness. The age of the vehicle can affect its performance and either ease or complicate the driving task. For example, an older car without driver assistance systems can relate with increased task complexity, while simultaneously, an older car being driven by the same driver may render the driving task easier due to the familiarity that has been gained by the driver. The number of Lane departure warnings can indicate the difficulty of the driving task, intuitively the higher the number, the greater the task complexity. Additionally, factors such as trip duration and distance travelled play a significant role for task complexity, with longer trips and greater distances potentially introducing fatigue and concentration challenges. Harsh events such as sudden braking, aggressive cornering, and rapid acceleration can serve as indicators of heightened task complexity, denoting interrupting flow of driving and quick adjustments from the driver. Month of the year can also impact task complexity, with seasonal variations influencing road conditions and traffic patterns. Similarly, the day of the week can relate with traffic conditions on the road, thus it can be linked with task complexity. Furthermore, headway measurement, reflecting the distance between vehicles, is crucial for the spatial dynamics of traffic and the cognitive demands placed on drivers. Finally, average speed can relate to task complexity, as higher speeds require rapid decision-making and increased vigilance. The interplay of these variables collectively shapes the intricate landscape of driving task complexity, underscoring the need for a comprehensive understanding of the factors involved.

Risk has been integrated as a latent variable within the model while headway and speed can serve as key variables. Headway and speed measurements are segmented into three levels corresponding to the STZ.

4. Results and discussion

4.1. SEM models

Four structural equation models were employed to explore the relationship of task complexity with headway related risk across the four phases of the UK on-road trial. The models were developed in IBM SPSS Amos 27 Graphics software and are presented in Table 3 (unstandardised coefficients). The path diagram of the phase 1 model displaying standardised coefficients is indicatively presented in Fig. 2. Maximum likelihood estimation method was employed, and non-statistically significant variables were excluded from the initial theoretical models. Throughout the analysis, one loading for each latent concept was fixed to a value of one, serving as a reference point for model identification purposes. The final models presented demonstrate a strong fit to the data. Details about the model fit can be found in Table 2.

The latent construct of task complexity is eventually represented by the indicator variables of vehicle age, day of week, the number of lane departure warnings per 30s, the use of high beams and the use of wipers.

Phase 1 of the road trial consisted of 53 drivers completing a total of 3073 trips, during which driving data were collected. This phase focused on observing the driving behaviour and patterns in the absence of any interventions or modifications, to provide a baseline measurement. In the model developed, all the observed indicators of the two latent variables task complexity and risk are statistically significant at 99.9 % confidence level. The latent variable of task complexity has a statistically significant positive effect on risk that is significantly interpreted by the time spent in each of the three levels of the STZ regarding the headway measurement. The more time a driver spends in the second and third level of STZ, i.e., closer to the vehicle in front for headway measurement, the higher the risk. Overall, increased task complexity relates

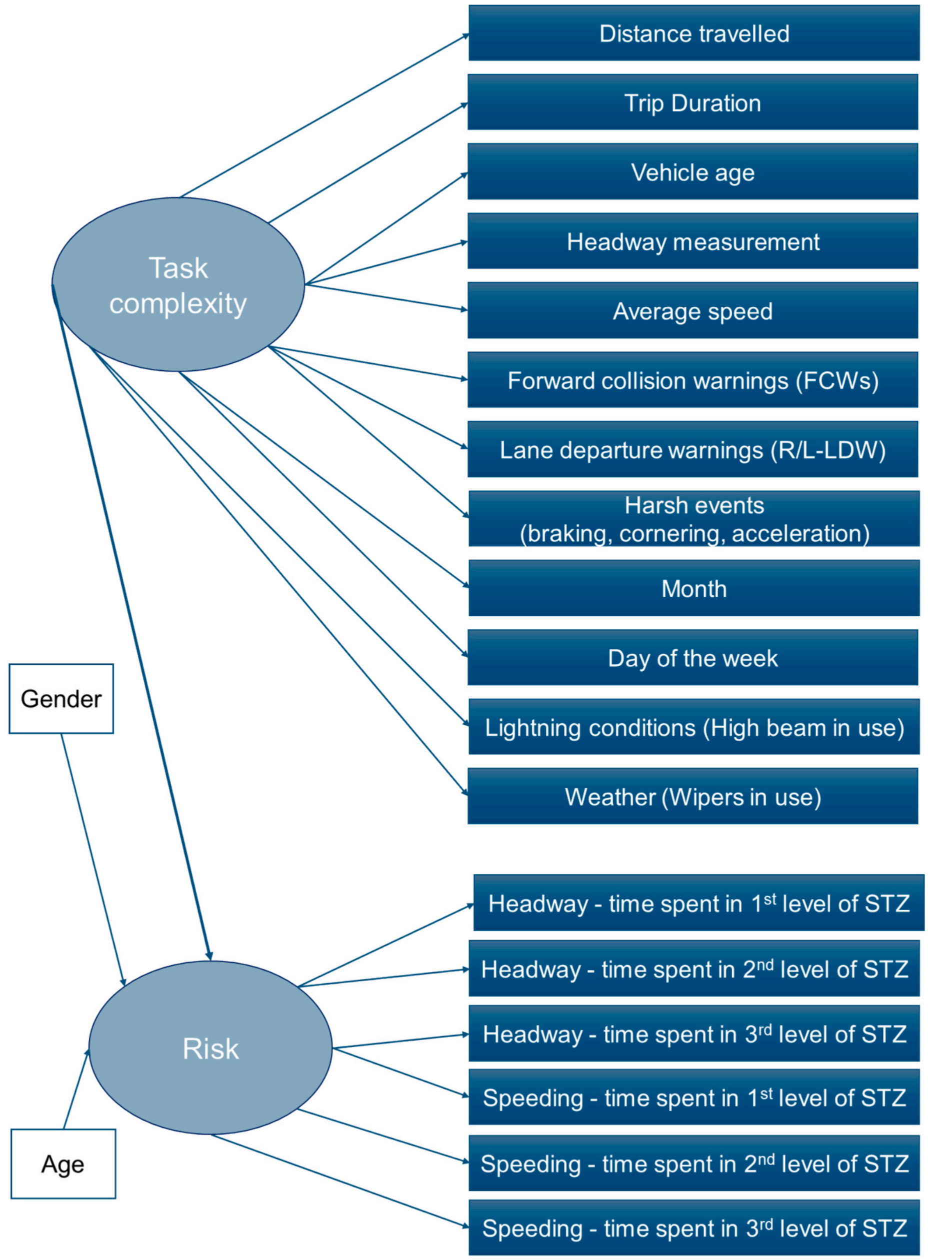

Fig. 1. Theoretical model of risk and task complexity.

to increased risk according to the model (standardised coefficient = 0.41).

In the model for Phase 1, task complexity relates positively with the number of LDWs,[1] the day of the week, the wipers and high beam use, and negatively with the vehicle age. According to the results, when wipers and high beam are in use, hence in rainy weather and in darkness, the task complexity is increased, which would be expected intuitively. Similarly, increased task complexity is related to the increased number of LDW per 30s, as expected, and the last days of the week. Fridays and weekends tend to be busy days of the week regarding traffic and the roads could be more congested [57,58], raising the levels of driving task demand.

Following the same approach, a SEM analysis was employed for driving data on Phase 2 of the on-road trials (54 drivers, 3317 trips) where interventions (real-time in vehicle warnings) have been introduced to the drivers. The observed indicators of task complexity and risk that remain statistically significant in Phase 2 are consistent with those identified in Phase 1, except for vehicle age. Task complexity continues to exhibit a positive and significant impact on risk (standardised coefficient = 0.53) translating to higher risk levels when task complexity increases. Increased levels of risk are similarly linked to higher time spent in the last two more critical levels of headway measurements of the STZ. The rest of the regression weights appear to be in correspondence with Phase 1, with number of right LDWs to be the predominant variable describing task complexity latent factor.

In Phase 3, involving a total of 53 drivers and 3417 trips, the drivers were provided with the opportunity to interact with the i-DREAMS smartphone application, to receive post-trip feedback in addition to the real-time warnings. In this phase, the variables related to wipers and high beam use did not demonstrate statistical significance as indicators of task complexity. However, the variable indicating the month

[1] Vehicles drive on the left in the UK meaning that right LDW indicate overtaking manoeuvres.

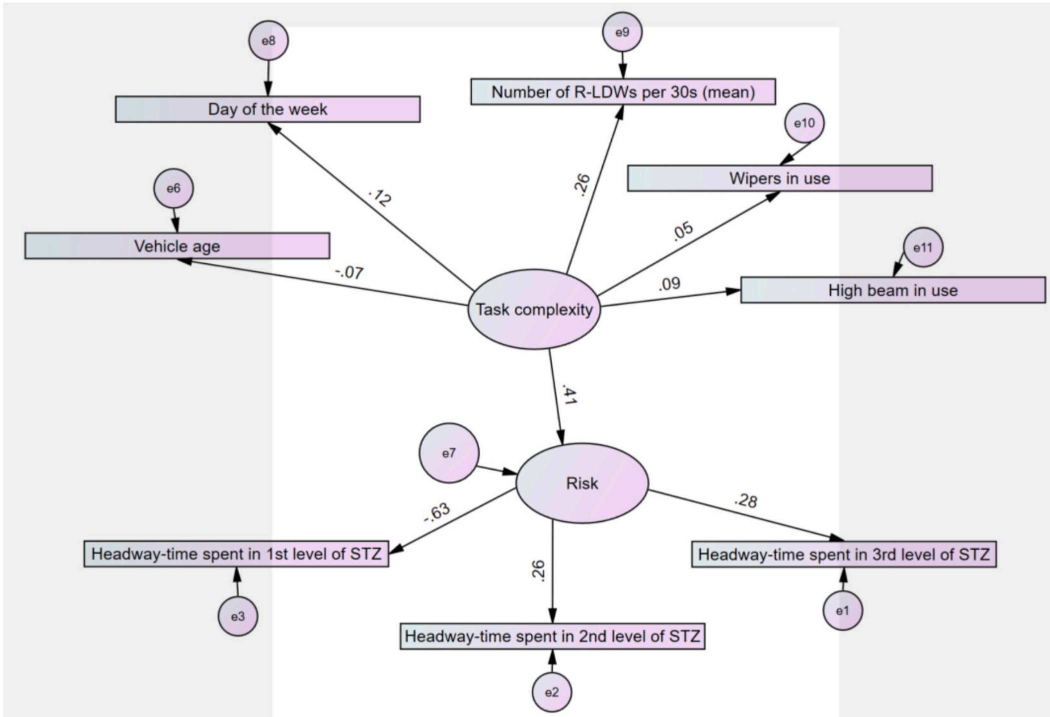

Fig. 2. Results of SEM Task complexity & Risk (headway STZ) - UK car drivers-experiment Phase 1.

Table 2
Model fit details for all phases.

Model fit summary	Phase 1	Phase 2	Phase 3	Phase 4
AIC	874	56	707.64	842.93
BIC	1038	326.73	833.58	995.09
CFI	0.906	0.896	0.923	0.905
TLI	0.862	0.831	0.856	0.846
RMSEA	0.019	0.024	0.027	0.018
GFI	0.998	0.998	0.998	0.999
HOELTER	0.5–4080	0.5–2915	0.5–2710	0.5–5171
	0.1–4899	0.1–3610	0.1–3511	0.1–6402

displayed statistical significance. This outcome can be attributed to the influence of traffic conditions and weather patterns during the time period of Phase 3 trials. Certain months may experience colder temperatures or higher precipitation, leading to task complexity being influenced by various factors such as frost, icy road surfaces, slippery pavements, and reduced visibility. Additionally, the pre-Christmas period or bank holidays can impose an effect on road traffic conditions, thereby affecting the demands of the driving task. Task complexity has a significant positive effect on risk as in the previous phases with the number of right LDWs to appear as the most significant indicator (higher standardised coefficient = 0.46) followed by the day of the week and month.

In Phase 4, involving a total of 54 drivers and 4594 trips, a key addition was the introduction of gamification features for the drivers, via the smartphone application, in addition to the real-time warnings and post-trip feedback. The model for the driver data in Phase 4 closely resembles that of Phase 2, as the same variables—wipers and high beam use, right LDWs, and day of the week—were all identified as significant. Notably, all observed indicators for the latent variables of task complexity and risk achieved statistical significance at a 99.9 % confidence level. Task complexity exhibited a statistically significant positive effect on risk (standardised coefficient = 0.32), which was significantly interpreted by the time spent in each of the three levels of the STZ regarding the headway indicator. Consistently with the findings from previous phases' models, longer driving duration in the first level of the STZ indicates lower levels of risk, while the positive relationship of task complexity with risk indicates that as the former increases, risk levels rise.

4.2. *Findings*

Overall, four SEM analyses were performed to assess the effect of task complexity on risk across the four phases of two waves on-road trials. The time that was spent in each level of the safety tolerance zone regarding the headway measurements were significant indicators of the latent construct of risk in all the phases. However, the variables that construct the latent concept of task complexity (these that were proved to be statistically significant) slightly differ from phase to phase. More specifically, the variables that remain significant across all phases are the number of right LDWs per 30s and the day of the week. Wipers and high beam in use variables were also consistently significant in three (1, 2, 4) out of the four phases - although the effect was smaller than this of the other variables - while vehicle age appears only in Phase 1 and month only in Phase 3. In all models across the trial, age and gender were not proven to be significant factors.

A rise in wipers and high beam use that could be translated to rain and low visibility conditions, the last days of the week probably denoting different traffic conditions, and an increased number of right lane departure warnings (could be indicative of demanding road layout, high cognitive workload) is linked to raised levels of driving task demand and this in turn results to higher risk levels. Last days of the week (weekends), except for different traffic density and composition, could be linked to higher consumption of alcohol or other substances that could affect task complexity and risk [59].

The results are aligned with previous literature regarding the effect of weather and darkness on driving task demand. More specifically, studies have proved that driving complexity increases by rain intensity or duration [29], as well as by rainfall height [30,31]. Similarly, darkness was shown to increase the task demand and crash risk [36].

The variable of month has a negative relationship with task

Table 3
Parameter estimates.

Phase 1	Estimate	S.E.	C.R.	p
Risk ← Task complexity	0.128	0.012	10.971	***
Headway-3rd level of STZ ← Risk	0.780	0.018	42.238	***
Headway-1st level of STZ ← Risk	−3.048	0.111	−27.471	***
Headway-2nd level of STZ ← Risk	1.000			
Vehicle age ← Task complexity	−1.042	0.128	−8.113	***
Day of the week ← Task complexity	1.000			
Number of R-LDWs ← Task complexity	0.428	0.036	11.814	***
Wipers in use ← Task complexity	0.059	0.009	6.441	***
High beam in use ← Task complexity	0.026	0.003	9.248	***
Phase 2				
Risk ← Task complexity	0.341	0.045	7.644	***
Headway-3rd level of STZ ← Risk	1.000			
Headway-1st level of STZ ← Risk	−4.300	0.152	−28.22	***
Headway-2nd level of STZ ← Risk	1.509	0.036	41.645	***
Day of the week ← Task complexity	2.529	0.228	11.073	***
Number of R-LDWs ← Task complexity	1.000			
Wipers in use ← Task complexity	0.183	0.028	6.616	***
High beam in use ← Task complexity	0.038	0.007	5.754	***
Phase 3				
Risk ← Task complexity	0.113	0.007	17.127	***
Headway-3rd level of STZ ← Risk	1.000			
Headway-1st level of STZ ← Risk	−2.795	0.093	−30.06	***
Headway-2nd level of STZ ← Risk	1.224	0.035	35.447	***
Number of R-LDWs ← Task complexity	1.000			
Month ← Task complexity	−3.056	0.180	−17.01	***
Day of the week ← Task complexity	2.854	0.153	18.711	***
Phase 4	Estimate	S.E.	C.R.	p
Risk ← Task complexity	0.090	0.006	15.380	***
Headway-3rd level of STZ ← Risk	1.000			
Headway-1st level of STZ ← Risk	−2.931	0.086	−33.97	***
Headway-2nd level of STZ ← Risk	1.644	0.043	38.531	***
Day of the week ← Task complexity	1.000			
Wipers in use ← Task complexity	0.033	0.007	4.929	***
Number of R-LDWs ← Task complexity	0.937	0.121	7.728	***
High beam in use ← Task complexity	0.025	0.002	10.617	***

*** Significant at 0.005 level.

complexity, thus the later in the year, the lower the task complexity in Phase 3 and this could be related to the two data collection waves and different traffic or weather conditions on different months of the year. A similar trend emerged in Phase 1, where older vehicles were linked to reduced task complexity. This outcome aligns with the notion that familiarity with one's vehicle increases over time, especially given the influx of distracting technologies in newer cars. Phase 1 was the only phase of the study where no warnings were provided to the drivers.

The number of right LDWs was the most representative indicator of task complexity (higher coefficient) in all four models. Lane changes undoubtedly contribute to task demand, and the association of a lane departure warning with an unindicated lane change suggests elevated cognitive load or abrupt manoeuvres.

The analysis consistently pointed to the positive impact of task complexity on risk, signifying that an increase in task complexity corresponds to an increase in risk. While the models mostly demonstrate similarities, the strength of this effect varied across phases, with Phase 2 showcasing the most substantial effect (standardised coefficient = 0.53). This could be possibly explained by the fact that in Phase 2 is the first time that the interventions are introduced to the drivers, which potentially augmented the driving task's complexity, contrasting with the later phases where participants had acclimated to the system.

The fact that driver demographics did not emerge as significant, underlining the importance of a systems approach focused on dynamic situational parameters for improving road safety. This comprehensive exploration on the dynamics between task complexity and driving risk on real-world settings identifies the main predictors of increased task demand, thereby pointing to high potential areas where interventions could target for risk mitigation on multiple levels.

This study's methodology and findings provide a transferable framework that can be adapted and applied in other countries to examine the relationship between task complexity and driving risk. It was part of a larger European project, where similar investigations were conducted in Greece, Portugal, and Belgium [60]. The use of SEM allows for the integration of locally relevant variables, facilitating comparisons across regions. By leveraging data from diverse contexts, this approach can uncover patterns and differences in driving behaviour, contributing to the global body of knowledge. Future research could apply this framework internationally to enhance the understanding of driving task complexity in relation to risk and improve global road safety.

5. Conclusions

This study aimed to probe the intricate relationship between task complexity and risk within the framework of a four phase on-road trial conducted in the UK. Utilising Structural Equation Modelling, the research shed light on the factors shaping task complexity and its relationship with risk. Both task complexity and risk were approached as latent concepts (not observable variables) in the study.

The findings underscore the positive correlation between task complexity and risk, particularly in relation to headway indicator. In other words, given the positive relationship, an increase in task complexity would be translated to an increase in risk. This contribution is important as it establishes the feasibility of identifying the relationship between risk and task complexity within a real-world driving study. Also of note, is the finding that older cars are associated with lower task complexity. This finding being observed only in phase 1 of this study also tentatively suggests that in-vehicle systems may in some cases amplify the task complexity, therefore careful consideration should be given to the design and features of these technologies.

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 utilised, leading to the use of proxies, i.e., the weather conditions were approximated by the use (or not) of wipers and the lighting conditions or night-time driving was determined by the use of high beams. Overall, collection of the intended variables proved more difficult than anticipated, leading to constrained data availability.

One limitation of this study is that it does not account for the influence of different types of road infrastructure, such as highways versus ordinary roads, on vehicle headway and speed. These factors are known to vary significantly depending on the driving environment, potentially impacting risk estimations. Due to constraints in the data collection, this trial had not collected such data, therefore this aspect was not included in the analysis. Future studies could explore this dimension to provide a more comprehensive understanding of risk in varying road environments. Nevertheless, this research's outcomes provide invaluable insights for future investigations, encouraging researchers to devise strategies to overcome similar data limitations.

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.

Moving forward, research in this domain could explore advanced data collection methods, such as leveraging vehicle sensor data and GPS tracking. By incorporating additional information, such as road configuration, traffic density, and other pertinent metrics, the precision of task complexity measurement could be significantly enhanced. This study's outcomes hold promise for informing road safety policies and interventions aimed at curbing road accidents and safeguarding lives. The identification of pivotal risk-contributing factors empowers policymakers and transportation authorities to devise targeted interventions and education initiatives addressing perilous driving behaviours. With the study unveiling the propensity of task complexity to elevate risk, there emerges a critical need to explore effective strategies for diminishing driving task demands. Advancing driver assistance systems with efficient and safer design, enhancing road infrastructure, and elevating driver training stand as tangible approaches towards achieving this goal.

Declarations of competing interest

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

CRediT authorship contribution statement

Evita Papazikou: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Rachel Talbot:** Writing – review & editing, Supervision, Conceptualization. **Laurie Brown:** Writing – review & editing. **Sally Maynard:** Writing – review & editing. **Ashleigh Filtness:** Writing – review & editing, Supervision.

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