# Which factors lead to driving errors? A structural equation model analysis through a driving simulator experiment


**Abstract**

As driving error is a main contributory factor of road accidents, its causes and consequences are of great interest in the road safety decision making process. This paper investigates several factors (including driver distraction, driver characteristics and road environment) that affect overall driving error behaviour and estimates a new unobserved variable which underlines driving errors. This estimation is performed with data obtained from a driving simulation experiment in which 95 participants covering all ages were asked to drive under different types of distraction (no distraction, conversation with passenger, cell phone use) in rural and urban road environment, as well as in both low and high traffic conditions. Driving error was then modelled as a latent variable based on several individual driving simulator parameters. Subsequently, the impact of several risk factors such as distraction, driver characteristics as well as road environment on driving error were estimated directly. The results of this complex model reveal that the impact of driver characteristics and area type are the only statistically significant factors affecting the probability of driving errors. Interestingly, neither conversing with a passenger nor talking on the cell phone have a statistically significant impact on driving error behaviour which highlights the importance of the present analysis and more specifically the development of a measure that represents overall driving error behaviour instead of individual driving errors variables.



**Keywords:** road safety, driving error, driving simulator, driver distraction, structural equation model

## INTRODUCTION

One of the most appropriate definitions regarding human factors error is proposed by Senders and Moray [1] who suggest that error is something that was done which was either: not intended by the actor; not desired by a set of rules or an external observer; or that led the task system outside of its acceptable limits. Human errors can therefore be defined as any mental or physical activity, or failure to perform activity, that leads to either an undesired or unacceptable outcome [2].

Driving error has long been a focus of road safety research. As a result, a range of methods have been developed to specifically measure this concept, including the Driver Behaviour Questionnaire [3] and the Wiener Fahrprobe method [4]. Estimates suggest that driving error is a causal factor in 75% [5], and in some cases even up to 95% [6] of road accidents and, thus, is a significant contributor to road accidents.

Hakamies-Blomquist [7] classified the direct causes of road accidents in four categories: incapacity of action, observation error, estimation error and driving error. Moreover, driving errors contributing to road accidents can be classified in four new categories: recognition errors (inadequate surveillance, internal distraction, and external distraction), decision errors (speeding, Illegal manoeuvre, aggressive driving) performance errors (overcompensation, Poor directional control) and critical non-performance errors (fatigue, sleeping, physical impairment) [6, 8].

In the last decades, there has been a large focus on investigating the connection between distraction and driving error, a link which is often not clear. In particular, there is no consensus regarding whether distraction is viewed as a driving error in itself or one of a number of causal factors that leads to errors [9]. The term distraction is defined as "a diversion of attention from driving because the driver is temporarily focusing on an object, person, task or event not related to driving, which reduces the driver's awareness, decision making ability and/or performance, leading to an increased risk of corrective actions, near-crashes, or crashes" [10].

A number of studies list distraction as the driving error, rather than as a causal factor [11, 12, 13]. These studies do not consider what the error type following the distraction episode is; thus, offering little insight into the nature of the errors associated with distracted driving. According to these studies, if a distracted driver was unable to stop at a red traffic signal, their failure to see the traffic signal following the distraction would not be captured; rather, the distraction itself would be listed as the error.

Other studies list distraction as a casual factor in driving errors, but do not investigate the mechanisms by which distraction contributes to driving errors [14, 15]. Wierwille et al. [15] list in-vehicle (mobile phone use, conversation with the passenger, eating/drinking, smoking etc.) and external (pedestrians, traffic control, advertising signs animals, etc.) distraction as one of the factors contributing to recognition errors, but do not indicate how distraction contributes to these errors. A thorough review of Young and Salmon [9] provides unique insights into the nature of errors made by distracted drivers under real-world driving conditions. The authors of this study stated that driving errors are common even under undistracted conditions but are significantly more pronounced when drivers are distracted. It was also revealed that the profile of errors made by distracted and undistracted drivers was very similar, suggesting that, at least for drivers distracted by a low demand visual task, the errors made differ in degree, but not in type compared to the errors made when not distracted.

Two more studies that have examined the nature of errors made by drivers found evidence that distraction is one of a number of factors that contribute to drivers committing errors [14, 16]. In an in-depth examination of 474 crashes, Staubach [14] found that a significant number of crossroads, lane departure and same direction crashes were the result of errors caused by the driver being distracted. Likewise, Sandin [16] sought to identify the factors underlying the most common errors and violations occurring at intersections (i.e., a failure to yield, or running a traffic light or sign). This report indicated that distraction contributed to a range of the errors occurring at intersections including missing a sign or traffic signal, misjudging the timing of amber lights, and a failure to see other vehicles.

Based on the above literature review on the scientific field of driving error and its relationship with driver distraction, some basic limitations can be identified. The first concerns the experimental process. Although the majority of driver distraction research has been performed with the use of driving simulators, as they allow for the examination of a range of driving performance measures in a controlled, relatively realistic and safe driving environment [17, 18] there are very few driving simulator experiments investigating driving errors. A second key finding concerns the statistical analysis methodologies implemented in driving performance and driving error studies. Latent model analysis and more specifically structural equation models have been very rarely implemented when investigating the causal factors of in the field of driving errors. This means that when the focus is on driving errors, most research studies determine individual performance parameters that are related to errors but cannot attribute them to an overall driving error behaviour.

Structural equation models (SEM) have been previously applied to many areas of transportation including transit system quality of service analysis [19], travel behavior modeling [20], mode choice modeling [21], driver behavior modeling [22] and public acceptability analysis of new technologies for traffic management [23]. SEM models may be viewed as a generalized case of multivariate classical statistical models and suffer from similar constraints as classical statistical models. However, they outperform other techniques due to their ability to treat auto-correlated errors, non-normal data and latent variables [19].

The objective of this paper is to investigate and quantify the effect of distraction (cell phone use and conversation with a passenger), driver as well as road environment characteristics in driving error within the framework of a driving simulator experiment. This study develops an innovative statistical analysis methodology, which consists of descriptive statistics, factors analysis as well as latent model analysis. In the next sections, the driving simulator experimental setup is described, and the statistical analysis methodology is presented. Finally, the results of the study are discussed, and future work is outlined.

# METHODOLOGY

## Sample

The driving simulator experiment included 95 participants, who started the driving simulator experiment (even if they didn't complete it). Table 1 presents the demographic, and experience distribution of the participants. It is shown that almost half of the participants are males (47) and half females (48) indicating that the there is a total balance in the sample regarding gender. Furthermore, in order to investigate age characteristics, three age groups were created. Out of the 95 participants, 28 were young drivers aged 18-34 years old, 31 were middle-aged drivers aged 35-54 years old and 36 older drivers aged 55-75 years old. In addition, the average years of education were 15.5 for the whole sample while the average years of driving were 25.5, indicating that the majority of participants were experienced drivers.

Table 1 Distribution of participants per age group and gender

| Age group | Female | | Male | | Total | | Years' Education | Years' Experience |
|---|---|---|---|---|---|---|---|---|
| 18-34 | 9 | 19% | 19 | 40% | 28 | 29% | 16 | 6 |
| 35-55 | 19 | 40% | 12 | 26% | 31 | 33% | 15 | 25 |
| 55+ | 20 | 42% | 16 | 34% | 36 | 38% | 14 | 37 |
| Total | 48 | 100% | 47 | 100% | 95 | 100% | - | - |

## Experiment design

The experiment took place within the framework of the "DISTRACT" research project, titled "Analysis of causes and impacts of driver distraction", which investigated endogenous and exogenous causes of driver inattention and distraction and their impacts on driver behaviour and safety [24]. The driving simulator experiment included different driving scenarios. The design of the distracted driving scenarios was a central component of the experiment and included driving in different road and traffic conditions, such as in a rural, urban area with high and low traffic volumes [25].

More specifically, the experiment included six individual trials on an urban driving session and another six individual trials on a rural driving session. These trials aimed to assess driving performance under typical conditions, with or without external distraction sources. The driving simulator experiment took place at the Department of Transportation Planning and Engineering of the National Technical University of Athens, where the Foerst Driving Simulator FPF was located. This driving simulator was a quarter-cab simulator with a motion base. The driving simulator consisted of 3 LCD wide-screen 40 in. (full high-definition), total angle view 170°, driving position, and support base. The dimensions at full development were 230 × 180 cm with a base width of 78 cm. It featured an adjustable driver seat, 27-cm-diameter steering wheel, pedals (throttle, brake, clutch), dashboard, and 2 external and one central mirror that appeared on the side and on the main screen and displayed objects and events that were happening behind the "vehicle" in real time.

The design and implementation of a large driving simulator experiment consisted the basis of the originality of the overall research and it was based on literature reviews aiming to deal with the majority of limitations that have been noted in the assessment of the examined simulator studies on driver distraction. The basic limitations found in the literature that the present experiment tackled were the following: a large and representative sample, randomization of driving trials, adequate practice drive and investigation of an optimum number of driving factors [26]. The overall methodological procedure consisted of the following steps:

<u>Instructions</u>
The first step of the procedure was to inform the participant orally and in writing about the full procedure of the experiment (completion of the questionnaire, total duration, driving preparation etc.). The need to maintain their usual driving behaviour without being affected from any other factors (stress, fear, etc.) was emphasized to the participants.

<u>Practice drive</u>
A familiarization session or "practice drive" is typically the first step of all driving simulator experiments. During the practice, the participant practiced handling the simulator (starting, gears, wheel handling etc.), keeping the lateral position of the vehicle, maintaining constant speed appropriate for the road environment as well as braking and stopping the vehicle. When all criteria mentioned above were satisfied (there was no exact time restriction), the participant moved on to the next phase of the experiment.

<u>Experimental process</u>
After the practice drive, each participant drove two sessions (~20 minutes each). Each session corresponded to a different road environment:

- A rural route that was 2.1 km long, with mixed traffic, lane width 3 m, zero gradient and mild horizontal curves (Figure 1).

Figure 1. Rural route

- An urban route that was 1.7km long, with mixed traffic, separated by guardrails, and lane width 3.5m. Moreover, narrow sidewalks, commercial uses and parking were available on the roadside (Figure 2).

Figure 2. Urban route

Within each area type, two traffic scenarios and three distraction conditions were examined in a full factorial within-subject design. The distraction conditions examined were driving while conversing with a passenger, driving while conversing on a cell phone and undistracted driving

The traffic demand scenarios were:

- $Q_L$: Moderate traffic conditions – with ambient vehicles' arrivals drawn from a Gamma distribution with a mean of 12 sec, and variance of 6 sec$^2$, corresponding to an average traffic volume of 300 vehicles/hour.
- $Q_H$: High traffic conditions – with ambient vehicles' arrivals drawn from a Gamma distribution with a mean of 6 sec, and variance $\sigma^2$=3 sec$^2$, corresponding to an average traffic volume of 600 vehicles/hour.

In total, each area (urban or rural) included six trials, i.e., six drives of the simulated route. In Table 2, the design parameters of the driving simulator experiment are summarized.

Table 2 Design parameters of the driving simulator experiment

| | Road Traffic Conditions | | | |
|---|---|---|---|---|
| | Urban Area | | Rural Area | |
| Distraction Sources | **$Q_L$** | **$Q_H$** | **$Q_L$** | **$Q_H$** |
| No Distraction | √ | √ | √ | √ |
| Cell Phone | √ | √ | √ | √ |
| Conversation With Passenger | √ | √ | √ | √ |

Furthermore, in order to remove bias and other sources of extraneous variation that are not controllable, randomization in the driving trials was implemented. In particular, randomization was used to determine which area type (urban/rural) the participant was going to drive, as well as in the order of the traffic scenarios and distraction scenarios presented to the driver. As a result, half of the participants drove first in the rural and then in the urban area while the rest drove first in the urban and then in the rural area.

Finally, as mentioned above, each driving trial introduced a different driving distraction factor and different level of traffic volume. The trials that included conversation as a distractor covered the following topics: family, origin, accommodation, travelling, geography, interests, hobbies, everyday life, news, business. One researcher was responsible for performing all the distraction tasks during the experiment by sitting as a passenger near the simulator or calling the participant on his mobile phone.

Questionnaire

After the driving simulator experiment, each participant was requested to fill in a questionnaire that included questions on their driving habits and behaviour. The questions were chosen carefully on the basis of the existing literature on drivers' self-reported behaviour [27, 28]. The sections of the questionnaire were: demographic characteristics, driving experience - car use, self–assessment, distraction-related driving habits, emotions and behaviour of the driver, anger expression inventory during driving, history of accidents, near misses, and traffic violations

**Analysis Methods**

To achieve the research an advanced analysis methodology has been developed exploiting a set of existing and advanced statistical models. The selected statistical analysis methods included the implementation of factor analysis as well as structural equation models.

An exploratory factor analysis is used in the early investigation of a set of multivariate data to determine whether the factor analysis model can provide a parsimonious way of describing and accounting for the relationships between the observed variables. Factor analysis is a close relative of principal components analysis. It was developed early in the twentieth century with the intent to gain insight into psychometric measurements, specifically the directly unobservable variable intelligence [29]. The aim of the analysis is to reduce the number of p variables to a smaller set of parsimonious $K<P$ variables. The objective is to describe the covariance among many variables in terms of a few unobservable factors. Factor analysis is related to principal component analysis (PCA), but the two are not identical. Latent variable models, including factor analysis, use regression modelling techniques to test hypotheses producing error terms, while PCA is a descriptive statistical technique [30].

Interpretation of factor analysis is straightforward. Variables that have high factor loadings are thought to be highly influential in describing the factor, whereas variables with low factor loadings are less influential in describing the factor. Inspection of the variables with high factor loadings on a specific factor is used to uncover structure or commonality among the variables. The underlying constructs that are common to variables that load highly on specific factors should then be determined [31]. For the purpose of the present study, a maximum likelihood (ML) factor analysis was developed through the factanal function in R Statistical program.

Within the present research, the scope of this analysis was to determine which observed variables are highly correlated with the common factor of driving error and how many common factors were needed to provide an adequate description of the data. In the second step of the overall methodology, structural equation models were used which belong to latent model analysis.

This type of analysis is used to deal with several difficult modeling challenges, including cases in which some variables of interest are unobservable or latent and are measured using one or more exogenous variables [31]. Structural equation models have two components, a measurement model and a structural model. Like factor and principal components analyses, SEMs rely on information contained in the variance-covariance matrix. Similar to other statistical models, the SEM requires the specification of relationships between observed and unobserved variables. Observed variables are measured, whereas unobserved variables are latent variables – similar to factors in a factor analysis – which represent underlying unobserved constructs

- The measurement model is used to determine how well various measured exogenous variables measure latent variables. A classical factor analysis is a measurement model and determines how well various variables load on a number of factors or latent variables. The measurement models within a SEM incorporate estimates of measurement errors of exogenous variables and their intended latent variable.
- The structural model represents how the model variables are related to one another. SEMs allow for direct, indirect, and associative relationships to be explicitly modeled, unlike ordinary regression techniques with implicit model associations. The structural component of SEMs enables substantive conclusions to be made about the relationship between latent variables and the mechanisms underlying a process or a phenomenon [31].

The basic equation of the latent variable model is the following [32]:

$$H = B\,\eta + \Gamma\,\xi + \zeta$$

in which $\eta$ (eta) is an ($m\times1$) vector of the latent endogenous variables, $\xi$ (xi) is an ($n\times1$) vector of the latent exogenous variables, and $\zeta$ (zeta) is an ($m\times1$) vector of random variables. The elements of the B (beta) and $\Gamma$ (gamma) matrices are the structural coefficients of the model; the B matrix is an ($m\times m$) coefficient matrix for the latent endogenous variables; the $\Gamma$ matrix is an ($m\times n$) coefficient matrix for the latent exogenous variables.

The basic equations of the measurement model are the following:

$x = \Lambda_x\xi + \delta$, for the exogenous variables,

$y = \Lambda_y\eta + \varepsilon$, for the endogenous variables

in which x and $\delta$ (delta) are column q-vectors related to the observed exogenous variables and errors, respectively; $\Lambda_x$ (lamda) is a ($q \times n$) structural coefficient matrix for the effects of the latent exogenous variables on the observed variables; y and $\varepsilon$ (epsilon) are column p-vectors related to the observed endogenous variables and errors, respectively; $\Lambda_y$ is a ($p\times m$) structural coefficient matrix for the effects of the latent endogenous variables on the observed ones.

Furthermore, a very useful tool for the interpretation of the results is path analysis. The quintessential feature of path analysis is a diagram showing how a set of explanatory variables can influence a dependent variable under consideration. The way the paths are drawn determines whether the explanatory variables are correlated causes, mediated causes, or independent causes. Finally, although model Goodness-of-Fit measures are an important part of any statistical model assessment, Goodness-of-Fit measures in SEMs are an unsettled topic, primarily as a result of lack of consensus on which Goodness-of-Fit measures serve as “best” measures of model fit to empirical data [33]. Several research studies are implemented discussing these debates and a multitude of SEM Goodness-of-Fit methods [34, 35,36]. One of the most common goodness-of-fit measures is standardized root average square residual (SRMR), which is an index of the average of standardized residuals between the observed and the hypothesized covariance matrices. Values of the SRMR range between zero and one, with well-fitting models having values less than 0.08 [32].

## RESULTS

The final dataset obtained from this study consisted of several types of variables regarding driver characteristics, parameters extracted from the questionnaire as well as parameters extracted from the driving simulator and included driving error and driving performance variables. Driver performance parameters included 23 numeric variables such as average speed, lateral position, reaction time etc. that are were included in the present research as they were out of the scope of this analysis. On the contrary, the driving simulator collected data in each trial for 7 variables that were defined as driving error variables and were used in the analysis.

Table 3 presents the type of each driving error variable, the minimum, maximum, and average values, per driving trial, giving a clear picture of the overall database that was used in the analysis. It should be noted that in total 438 trials were implemented by the participants.

Table 3. Variables' characteristics

| Variable | Description | Type | Min | Max | Average |
|---|---|---|---|---|---|
| Hit Of Side Bars | how many times per trial, the vehicle hit the sidebars in the right | Integer | 0,00 | 8,00 | 0,39 |
| Outside Road Lines | how many times per trial, the vehicle crossed over road lines | Integer | 0,00 | 2,00 | 0,01 |
| High Rounds Per Minute | how many times per trial, the rounds per minutes of the motor exceeded 5000 | Integer | 0,00 | 13,00 | 0,34 |
| Sudden Brakes | how many times per trial, the driver braked suddenly | Integer | 0,00 | 9,00 | 2,32 |
| Speed Limit Violation | how many times per trial, the vehicle exceeded the speed limit | Integer | 0,00 | 6,00 | 0,19 |
| Engine Stops | how many times per trial, the engine of the vehicle stopped | Integer | 0,00 | 11,00 | 1,05 |
| Slow Rounds Per Minute | how many times per trial, the rounds per minutes of the motor were less than 1000 | Integer | 0,00 | 4,00 | 0,11 |

In the first step, a factor analysis was implemented in which seven driving performance variables were considered. Table 4 presents the loadings of the respective variables, which indicate how much each variable explains the driving error factor.

Table 4. Driving error factor analysis loadings

| Variables | Loading |
|---|---|
| Hit of Side Bars | 0.54 |

| | |
|---|---|
| Outside Road Lines | 0.44 |
| High Rounds Per Minute | 0.43 |
| Sudden Brakes | 0.17 |
| Speed Limit Violation | 0.08 |
| Engine Stops | 0.14 |
| Slow Rounds Per Minute | 0.22 |

**Summary statistics**

| | |
|---|---|
| ss loadings | 0.73 |
| proportion var | 0.10 |
| cumulative var | 0.36 |
| Test of the hypothesis that 1 factor is sufficient | |
| chi square statistic | 104.7 on 14 degrees of freedom |
| p-value | 5.91e-16 |

| | **factor 1** |
|---|---|
| Interpretation | Driving error |

The results indicated that the hypothesis test that one factor can underline participant driving errors is true. The specific variables that have the highest loadings in this factor analysis, i.e., the ones that tend to better explain the new 'Driving Error" factor were the "Hit of Side Bars", "Outside Road Lines", and "High Rounds per Minute".

As discussed earlier, factor analysis was the first step of the overall analysis aiming to estimate which variables obtained from the driving simulator experiment have the biggest estimated impact on the unobserved driving error variable. In the second and most important step of the analysis, driving error was defined as a new unobserved variable for latent analysis purposes and SEMs were used for the investigation of the effect of driver, road, and traffic characteristics, as well as driver distraction directly on driving error. The estimation results of the SEM are presented in Table 4.

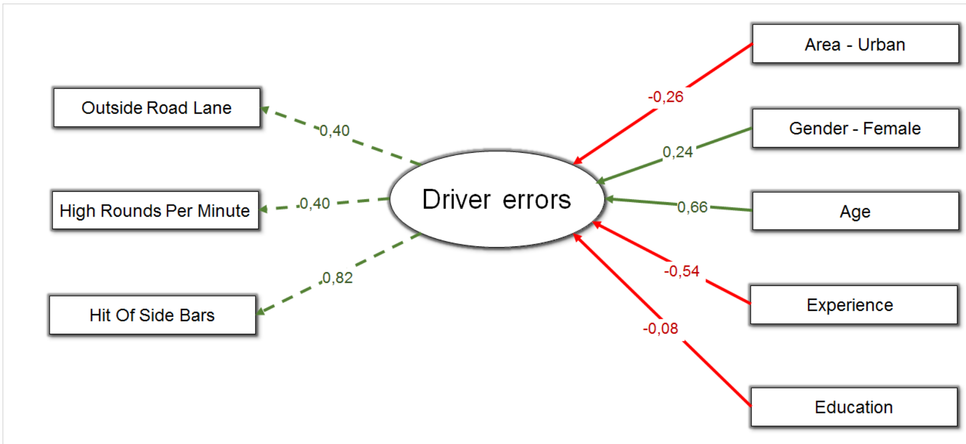
Table 4 Estimation results of the driving error SEM

| | **Estimate** | **Std Error** | **t-value** | **P(>\|z\|)** |
|---|---|---|---|---|
| **Driving Error** | | | | |
| Hit Of Side Bars | 1.000 | - | - | - |
| Outside Road Lanes | 0.741 | 0,257 | 2.887 | 0.004 |
| High Rounds Per Minute | 0.680 | 0,243 | 2.803 | 0.005 |
| **Regression** | | | | |
| Driving errors | | | | |
| Gender - Female | 0.359 | 0,076 | 4.739 | 0.000 |
| Age | 0.031 | 0,009 | 3.393 | 0.001 |
| Area - Urban | -0.393 | 0,062 | -6.383 | 0.000 |
| Experience | -0.030 | 0,010 | -3.050 | 0.002 |
| Education | -0.021 | 0,010 | -2.167 | 0.030 |
| **Summary statistics** | | | | |
| Minimum Function Test | 62.19 | | | |
| Degrees of freedom | 10 | | | |
| **Goodness of fit** | | | | |
| SRMR | 0.032 | | | |

It is shown that the unobserved (latent) variable which reflected driving error was estimated based on three variables: how many times per trial, the vehicle hit the sidebars in the right, how many times per trial, the vehicle crossed over road lines and how many times per trial, the rounds per minutes of the motor exceeded 5000.

The obtained value of SRMR (0.032) for this model is statistically accepted (<0.08) proving that the overall SEM is suitable. The path diagram of the developed model is presented in the Figure 3. It should be noted that green lines express a positive correlation between the variables while red lines express a negative one. Furthermore, dashed lines indicate which variables create the latent one (first part of the SEM) while continuous lines indicate which variables exist in the regression part of the SEM. Finally, the label values represent the standardized parameter estimates.

Figure 3 Path diagram of the driving error SEM




Model results indicated that driving error (latent variable) was positively correlated by three driving simulator variables (number of hit of side bars, number of outside road lanes, and number of high rounds per minute) as represented by the dashed lines of the figure above. It should be noted that the creation of the unobserved variable was in absolute agreement with the respective explanatory factor analysis presented earlier.

For the structural part of the SEM, driving error was the dependent variable while the independent variables included road environment characteristics (area type) as well as driver characteristics (age, gender, experience, education). It is also important to mention that several SEM attempts took place before coming to the final model pesented above. In these attempts several other variables were not found to have a statistically significant effect on the model and were omitted on the final one. These included the distraction sources examined during the experiment and traffic characteristics.

Interpretating the results, an interesting finding is the absence of distraction factors indicating that neither conversing with a passenger nor talking on the cell phone has a statistically significant impact on driving errors. This finding however does not indicate that the examined driver distraction sources do not lead drivers to committing errors at all. Driver distraction may contribute to errors through a range of means: by affecting cognitive processes such as perception, planning, decision making, and situation awareness, as well as by interfering with vehicle control tasks. However, based on the findings of this study the effect of driver characteristics as well as area type is much higher than the effect of distraction on driving errors.

Female as well as older drivers were found to be more prone to driving errors, while the parameters of experience as well as education were, as expected, countervailing factors regarding driving errors. Finally, the road environment results reveal that traffic conditions do not have a statistically significant effect on driving errors, while in rural areas drivers are more likely to get involved in risky driving situations due to their own driving errors.

## CONCLUSIONS

Overall, the proposed methodological approach and statistical techniques of the present research provide new insights on driver behaviour and safety. The added value of the methodology, through the consideration of latent variables and the implementation of SEMs, is found to be useful and promising [25], allowing in the present research to explore a new approach to the investigation of driving error.

Focusing on driver distraction, a first very interesting finding of the present research is that, neither conversing with a passenger nor talking on the cell phone have a statistically significant impact on driving error compared with other driver and road characteristics. This finding which was not previously identified in the literature highlights the importance of the present analysis and more specifically the development of a measure that represents overall driving error behaviour instead of individual driving errors. In Young and Salmon [9], where a critical review examining the relationship between driver distraction and driving errors took place, the authors examined several papers where individual driving errors have been assessed (i.e. wrong action, wrong assumption, failure to observe, misunderstood information etc.). The authors state that although it makes intuitive sense that being distracted can lead to drivers making a range of errors, there is currently a limited understanding of the relationship between driver distraction and driver error and how other factors, such as environmental, vehicle or road infrastructure design, can moderate this relationship. For example, Sandin [16] found that distraction contributed to a range of errors occurring at intersections including missing a sign or read traffic signal, misjudging the timing of amber lights, and failure to see other vehicles. Other taxonomies do list distraction as a casual factor in driver errors, but do not indicate the mechanisms by which it contributes [14, 15].

Based on the above, there is no research investigating the effect of distraction on overall driving error behaviour and this is a very critical finding of the current research which supports the fact that neither conversing with a passenger nor talking on the cell phone have a statistically significant impact on driving errors. Consequently, the increased accident risk of distracted driving may be due to other factors than their errors (e.g. inability to cope with the errors of other drivers or other unexpected incidents).

On the other hand, this study confirms the initial hypothesis that driving error is deeply correlated with driver characteristics [37, 38, 39]. More specifically, gender, age, education as well as driving experience were shown to have the highest effect on driving error in the present research. Gender and age have a positive sign indicating that female drivers as well as older drivers are more likely to perform driving errors. Furthermore, young drivers have better mental and physical characteristics than older drivers reducing their likelihood of commiting errors even when distracted. On the other hand, both drivers' experience and education have a negative sign indicating that a more experienced and more educated driver is less likely to perform driving errors. This finding probably means that both these driver characteristics help the driver properly handle a potentially hazardous situation and protect him from committing an error.

With regards to the driving environment only the area type was found to significantly affect driving errors as in rural areas drivers are more likely to get involved in risky driving situations.

This finding is in line with the literature [40] and indicates that in rural area drivers achieve higher speed compared to urban areas and in addition may be less concentrated due to the usually longer duration of their trips, leading to driving errors.

Based on the above and considering that by the successful implementation of SEMs, driving error behaviour is assessed in terms of the overall performance and not through individual measures, a direct contribution relies on the development of a driving profile that is more prone on committing driving errors. More specifically, more likely to commit errors are female older drivers with low education level and low experience driving in rural area. This finding can potentially contribute to a significant reduction of road accidents and fatalities, if it will be exploited by the authorities to implement appropriate road safety policy directions focusing on driving error behaviour.

The next steps of the present research include further developing the structural equation models and applying them in more general driving behaviour scientific fields. As an example, the effect of several other parameters such as fatigue or alcohol can be estimated on the unobserved variables, which underline driving performance or accident risk. In addition, several other latent variables can be created and examined (e.g., accident risk), by developing appropriate experiments that can assist with answering specific research questions.

**ACKNOWLEDGMENT**

This paper is implemented within the framework of "IKY Fellowships of Excellence for Post-graduate studies in Greece - Siemens Program".

**REFERENCES**

1. J. Senders, N. Moray, Human error: Cause, prediction and reduction. Lawrence Erlbaum Associates, Hillsdale, New Jersey, 1991
2. P. Salmon, K. Young, M. Lenné, A. Williamson,N. Tomesevic, To err (on the road) is human? An on-road study of driving errors. In: Australasian Road Safety Research, Policing and Education Conference, Canberra, Australia, 2010
3. J. Reason, Human Error. Cambridge University Press, Cambridge, 1990
4. R. Risser, C. Brandstätter, Die Wiener Fahrprobe: Freie Beobachtung, Kleine Fachbuchreihe des Kuratoriums für Verkehrssicherheit, Band 21, 1985
5. J. Hankey, W. Wierwille, W. Cannell, C. Kieliszewski, A. Medina, T. Dingus, Identification and evaluation of driving errors: Task C report, driving error taxonomy development (Draft Technical Report). Project No. DTFH-61-97-C-00051. Virginia Tech, Center for Transportation Research, Blacksburg, VA, 1999
6. K. Rumar, The basic driving error: late detection. Ergonomics 33(1990), 1281-1290.
7. L. Hakamies-Blomquist Fatal accident of older drivers. Accident Analysis and Prevention, 25 (1993), 19–27
8. J. Treat, A study of precrash factors involved in traffic accidents, HSRI Research Review, 10 (1980), 1–35.
9. K. Young P. Salmon, Examining the relationship between driver distraction and driving errors: A discussion of theory, studies and methods. Safety Science, 50 (2012), 164-175

10. K. Young, M. Regan, Driver distraction: A review of the literature. In: I.J. Faulks, M. Regan, M. Stevenson, J. Brown, A. Porter & J.D. Irwin (Eds.). Distracted driving. Sydney, NSW: Australasian College of Road Safety. 379-405, 2007
11. J. Reason, A. Manstead, S. Stradling, J. Baxter, K. Campbell, Errors and violations on the roads: a real distinction? Ergonomics 33 (1990), 1315–1332.
12. B. Sabey, G. Staughton, Interacting roles of road environment, vehicle and road user in accidents. In: Paper Presented at the 5th International Conference of the International Association of Accident and Traffic Medicine, London, UK, 1975
13. B. Sabey, H. Taylor, The known risks we run: the highway. In: Schwing, R.C., Albers Jr., W.A. (Eds.), Societal Risk Assessment: How Safe is Safe Enough? Plenum Press, New York, NY, 1980
14. M. Staubach, Factors correlated with traffic accidents as a basis for evaluating Advanced Driver Assistance Systems. Accident Analysis & Prevention 41 (2009), 1025–1033.
15. W. Wierwille, R. Hanowski, J. Hankey, C. Kieliszewski, S. Lee, S. Medina, Identification and evaluation of driving errors: overview and recommendations. Report no. FHWA-RD-02-003. U.S Department of Transportation, Federal Highway Administration, Washington, DC, 2002
16. J. Sandin, An analysis of common patterns in aggregated causation charts from intersection crashes. Accident Analysis & Prevention 41 (2009), 624–632.
17. M. Regan, J. Lee, K. Young, Driver Distraction: Theory, Effects, and Mitigation. CRC Press Taylor & Francis Group, Boca Raton, FL, USA, 31–40, 2008
18. E. Chan, A. Pradhan, A. Pollatsek, M. Knodler, D. Fisher, Are driving simulators effective tools for evaluating novice drivers' hazard anticipation, speed management, and attention maintenance skills?, Transportation Research Part F: Traffic Psychology and Behaviour, 13 (2010), 343-353
19. M. Karlaftis, I. Golias, E. Papadimitriou, Transit Quality as an Integrated Traffic Management Strategy: Measuring Perceived Service, Journal of Public Transportation, 4 (2001), 27-44.
20. T. Golob, Structural equation modeling for travel behavior research. Transportation Research Part B: Methodological 37 (2003), 1–25
21. M. Johansson, T. Heldt, P. Johansson, The effects of attitudes and personality traits on mode choice Transportation Research Part A, 40 (2006), 507–525.
22. H. Hassan, N. Abdel-Aty, Analysis of drivers' behavior under reduced visibility conditions using a Structural Equation Modeling approach, Transportation Research Part F, 14 (2011), 614–625.
23. Y. Chung, T. Song, J. Park, Freeway booking policy: Public discourse and acceptability analysis Transport Policy, 24 (2012), 223–231
24. G. Yannis, S.G. Papageorgiou, A. Economou, E. Papadimitriou S. Vardaki, P. Papantoniou D. Pavlou J. Golias, N. Andronas, A. Liozidou, I. Beratis, Design of a Large Driving Simulator Experiment on Performance of Drivers with Cerebral Diseases, Proceedings of the 4th International Conference on Road Safety and Simulation, Rome, 2013
25. P. Papantoniou, Structural Equation Model analysis for the evaluation of overall driving performance: A driving simulator study focusing on driver distraction, Traffic Injury and Prevention, 19(3) (2018) 317-325
26. P. Papantoniou, E. Papadimitriou, G. Yannis, Assessment of Driving Simulator Studies on Driver Distraction, Advances in Transportation Studies, 35, 2015, 129-144.

27. S. Vardaki, M. Karlaftis, An investigation of older driver road safety perceptions and driving performance on freeways. 3rd International Conference on Road Safety and Simulation, Indianapolis, USA, 2011
28. T. Lajunen, H. Summala, Driver experience, personality, and skill and safety motive dimensions in drivers' self-assessments. Personality and Individual Differences, 19 (1995), 307-318
29. R. Johnson, D. Wichern, Multivariate Statistical Analysis, 3rd ed. Prenticehall, Englewood Cliffs, NJ., 1992
30. D. Bartholomew, F. Steele, J. Galbraith, I. Moustaki, Analysis of Multivariate Social Science Data (2 ed.). New York:Chapman & Hall/Crc, (2008)
31. S. Washington, M. Karlaftis, F. Mannering, Statistical and econometric methods for transportation data analysis. CRC press, 2010
32. F. Chen, Sensitivity of goodness of fit indexes to lack of measurement invariance. Struct Equ Modeling. 14 (2007) 464–504.
33. J. Arbuckle, W. Wothke, AMOS User's Guide. Version 4.0. Small Waters Corporation, Chicago, IL, 1995
34. S. Mulaik, L. James, J. Van Alstine, N. Bennett, S. Lind, C. Stilwell, Evaluation of goodness of fit indices for structural equation models. Psychological Bulletin 105 (1989), 430-445.
35. R. MacCallum, The need for alternative measures of fit in covariance structure modeling. Multivariate Behavioral Research 25 (1990), 157-162.
36. J. Steiger, Structural model evaluation and modification: An interval estimation approach. Multivariate Behavioral Research 25 (1990), 173-180.
37. B. Gonzalez-Iglesias, J, Gomez-Fraguela, M. Luengo-Martın, Driving anger and traffic violations: Gender differences. Transportation Research Part F: Traffic Psychology and Behaviour, 15(4), (2012) 404–412.
38. T. Ozkan, T. Lajunen, H. Summala, Driver behaviour questionnaire: A follow-up study accident analysis & prevention. Accident Analysis and Prevention, 38(2), (2006) 386–395.
39. C. Wickens, M. Toplak, D. Wiesenthal, Cognitive failures as predictors of driving errors, lapses, and violations. Accident Analysis and Prevention, 40, (2008) 1223–1233.
40. D. Pavlou, Traffic and safety behaviour of drivers with neurological diseases affecting cognitive functions (unpublished doctoral dissertation). National Technical University of Athens, 2015