Are driving errors and driving performance correlated? A dual structural equation model

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Abstract

The present paper aims to investigate whether, and if yes how, driving errors are correlated with the driving performance. To this end, both errors and performance are considered unobserved (latent) variables that are modeled using a structural equation modeling approach to reveal the critical factors that may affect driving performance, including driving error. The data come from a driving simulator experiment, in which 95 participants from all age groups were asked to drive 12 driving trials under different types of distraction (no distraction, conversation with passenger, cell phone use) in rural/urban road environment, in low/high traffic. Findings indicate that, neither road characteristics (area type, traffic conditions), nor the distraction sources examined (cell phone use, conversation with a passenger) have a significant impact on driving performance as driving error and driver characteristics. Finally, regarding driver characteristics, age, gender and driving experience have the highest impact on the overall driving performance.

Keywords – driving error, driver distraction, driver performance, structural equation model

1. Introduction

The relationship between driving error and driving performance has been systematically highlighted as a key priority for road safety research considering that driving error is a causal factor in 75% [1], or even up to 95% [2] of road accidents. Within this framework, several experimental procedures (i.e. driving simulator, naturalistic and on-road experiments) and various individual measures exist both regarding driving performance, as well as driving error [3].

The state-of-the-art sees driving performance as a multidimensional phenomenon, which means that no single driving performance parameter can capture all aspects of the overall driving performance [4]. Most research attempt to investigate specific driving performance variables, such as longitudinal control measures, lateral control measures, reaction time, gap acceptance etc. disregarding the multidimensional nature of the phenomenon [5-7]. The selection of the specific measures that define overall performance should be guided by a rule of representativeness between the selected variables. Papantoniou [8] estimated the overall driving performance based on a longitudinal measure (i.e. speed), a lateral measure (i.e. standard deviation of the lateral position), a reaction time measure (i.e. the time until the road border line is exceeded) and average gear of the vehicle.

Focusing on driving error, one of the most appropriate definitions regarding human factors error, in relation to the present research, was proposed by Senders and Moray [9] who suggested that error is something that has been done which was either: not intended by the actor; not desired by a set of rules or an external observer; or that lead 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 [10]. Hakamies-Blomquist [11] 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 (i.e. inadequate surveillance, internal distraction, and external distraction), decision errors (i.e. speeding, illegal overtaking, tailgating, aggressive driving), performance errors (i.e. overcompensation, poor directional control) and critical non-performance errors (i.e. fatigue, sleeping, physical impairment) [12].

Overall, the aim of the work documented in this paper addresses two key objectives. The first is to investigate whether driving performance and driving error are correlated and, the second, to revisit the effect of several risk factors including distraction sources, driver characteristics, road and traffic environment, as well as driving error behavior on overall driving performance. For this, a unified modeling framework based on structural equation models is developed using data collected by a large-scale driving simulator study.

The paper follows the structure outlined below: Following the introduction section, a theoretical background of the correlation of driving performance and driving error is included in the background. In the next sections, the driving simulator experimental setup is described, and the statistical analysis methodology is presented. Then, the results of the study are detailed outlined and a discussion of the key outputs is also provided. Finally, at the end of this paper, along with the limitations and the future research directions, some main conclusions of the present work are summarized.

2. Background

Structural Equation Models (SEMs) have been widely used for modelling road user behavior and safety. This type of analysis has already been applied to many areas of transportation, including transit system quality of service analysis [29], travel behavior modelling [30], mode choice modelling [31], driver behavior modelling [32], public acceptability analysis of new technologies for traffic management [33], traffic spatio-temporal analysis at the emergence of an incident [34] and Powered Two-Wheelers overtaking modelling [35]. SEMs may be viewed as a generalized case of multivariate classical statistical models and suffer from similar constraints as classical statistical models but outperform other techniques due to their ability to treat auto-correlated errors, non-normal data and latent variables [29]. In addition, the self-reported behavior of car drivers [13], motorcyclists [14] or pedestrians [15] are typically modelled in relation to other human factors (i.e. attitudes, behavior, motivations) or external factors. SEM has been used to model other behavioral aspects in the form of latent variables e.g. driving anger [16], speeding behavior [17], or perceived risk.

Dimitriou et al. [18] made a cluster analysis to group countries and developed a set of SEMs to model global mortality statistics (in terms of mortality rates per population, per vehicle fleet) in relation to various socioeconomic constructs (i.e. economy, demographics, road network and traffic enforcement characteristics). Moreover, Zhao et al. [19] used a similar approach to model driving performance as a latent variable measured by means of driving simulator metrics and developed a SEM associating it with factors of driver characteristics, illegal actions and attitudes – these “independent” variables came from a combination of simulator and questionnaire metrics.

Useche et al. [20] developed SEM to describe relationships between risky behaviors, risk perception, knowledge of traffic norms and cycling intensity (all latent constructs on the basis of a structured questionnaire) and the self-reported cycling crash frequency in the last 5 years. An earlier study of the same authors [21] focused on the differences of risky cycling behavior as a latent variable between male and female cyclists. Meuleners and Fraser [22] attempted to validate a laboratory-based driving simulator in measuring on-road driving performance by type and mean driving errors. For this purpose, 47 participants were instructed to drive a selected route on-road and a similar route in the driving simulator. Results indicated that there was no statistical difference between the on-road assessment and the driving simulator for mirror checking, left, right and forward observations, speed at intersections, maintaining speed, obeying traffic lights and stop signs.

Additionally, several studies focused on distraction related factors. It makes sense that being distracted can lead to driving errors. However, the link between distraction and different error types was often not clear, particularly regarding whether distraction was viewed as a driving error or a causal factor that led to errors [23]. In several studies, distraction was a causal factor in driving errors, but without indicating the mechanisms by which it contributed [24]. For instance, Wierwille et al. [25] listed internal and external distraction as one of the factors contributing to recognition errors, but did not indicate how distraction contributed to these errors.

Furthermore, the mechanisms underlying the relationship between distraction and error were not clear enough and more precise knowledge was needed [23]. Specifically, authors reported several under-researched issues, including the number and nature of errors made by drivers when distracted; the mechanisms by which distraction caused errors; whether and how distraction disrupted drivers' ability to recover from errors; and how system-wide factors moderated the relationship between distraction and error. Similarly, Young et al. [26] stated that although driving errors were part of everyday driving behavior even under undistracted conditions, driving errors were significantly more pronounced, when drivers were 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-manual task, the errors made differ in degree, but not in type to the errors made when not distracted.

3. Methodology

3.1. Driving simulator

Within the present research, a driving simulator experiment took place including different driving scenarios. The driving simulator belongs to the Traffic Engineering Laboratory of the National Technical University of Athens (NTUA) and consists of 3 LCD wide screens 40'' (full HD), total angle view 170 degrees, driving position and support base. The dimensions at a full development are 230x180 cm with a base width of 78 cm. It features adjustable driver seat, steering wheel 27cm diameter, pedals (throttle, brake, clutch), dashboard and two external and one central mirror that appeared on the side and on the main screen, and display in real time objects and events that are occurring behind the 'vehicle'. The controls available to the driver are: 5 gears plus reverse gear, flash, wipers, lights, horn, brake and starter. Figure 1 illustrates a schematic overview of the experimental driving simulator.

Fig. 1: Experimental Driving Simulator

3.2. Sample characteristics

With regards to the framework of the current study, 111 participants started the driving simulator experiment. Almost 18% (16 participants) were eliminated from the study because they had simulator sickness issues from the very beginning of the driving simulator experiment. It is worth mentioning that in spite of its strengths, driving simulator experiments face certain limitations which shall be considered. To begin with, many participants reported feeling ill while using the driving simulator device [34]. This ill feeling which has been reported in both fixed and motion-based driving simulators was referred to as simulation sickness [35, 36]. Moreover, simulation sickness can result in severe symptoms in participants including eye strain, headache, postural instability, sweating, disorientation, vertigo, pallor, nausea, and vomiting. It can also severely influence the behavior and performance of participants and thus can lead to invalid results. Participants may lose their motivation and ability to concentrate, avoid tasks that are found disturbing, or even modify their behavior to reduce sickness symptoms.

As a result, 95 participants consisted the sample of the driving simulator experiment while almost half of the participants were males (47) and half females (48) indicating that the there is a total balance in the sample regarding gender. Furthermore, 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 driver aged 55-75 years old. In addition, the average years of education were 12 for the whole sample while the average years of driving 23.06 indicating that most participants were experienced drivers.

It should be noted that people who participated in the present experiment, did not go through any Institutional Review Board; however, they met certain basic criteria. More specifically each participant should have a valid driving license, have driven for more than 3 years, have driven more than 2500km during the last year, have driven at least once a week during the last year and have driven at least 10km/week during the last year.

3.3. Experimental design

The present work employed an experimental design procedure, which aimed to deal with the majority of limitations revealed through literature research, such as having a large and representative sample, the randomization of driving trials, the adequate practice drive and the investigation of an optimum number of driving factors [37]. The overall experimental procedure consisted of two different road environments as presented below:

- A rural route that was 2.1 km long, with mixed traffic, lane width 3 m, zero gradient and mild horizontal curves (Figure 2)
- An urban route that was 1.7 km long, with mixed traffic and lane width 3.5 m. Moreover, narrow sidewalks, commercial uses and parking were available on the roadside (Figure 3)

Fig. 2: Rural route selected in the experiment

Fig. 3: Urban route selected in the experiment

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. Moreover, the traffic scenarios were:

- QL: Low 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.
- QH: High traffic conditions – with ambient vehicles' arrivals drawn from a Gamma distribution with a mean of 6 sec, and variance σ^2=3 sec^2, corresponding to an average traffic volume of 600 vehicles/hour.

Furthermore, to remove bias and other sources of extraneous variation that are not controllable, randomization in the driving trials was implemented. Randomization was used to determine which area type (urban/rural) the participant was going to drive first. Consequently, participants were randomly assigned to the respective road environments.

3.4. Experimental procedure

The experiment encompasses four different tasks. During the first task, the participant was informed 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 behavior without being affected from any other factors (i.e. stress, fear) was emphasized to the participants.

The second task was the familiarization stage (practice drive) during which 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.

Following the practice drive, the last task involved the "real" driving, which was the part that was further used in the analysis. Each participant drove around 40 minutes. During this procedure, 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. Topics covered included: family, origin, accommodation, travelling, geography, interests, hobbies, everyday life, news, business.

In the fourth task, following the simulator experiment, each participant was requested to fill in a questionnaire that included questions on their driving habits and behavior. The questions were chosen carefully based on the existing literature on drivers' self-reported behavior [38]. The sections of the questionnaire were: self–assessment, distraction-related driving habits, emotions and behavior of the driver, anger expression inventory during driving, history of accidents, near misses, and traffic violations. However, for the purpose of the present analysis, only parameters regarding the participants' characteristics were taken into consideration.

3.5. Analysis method

It should be noted that SEMs belong to the latent model analysis and are ideal for modelling complex multi-dimensional problems, including cases in which some variables of interest are unobservable or latent and are measured using one or more exogenous variables [39]. Moreover, SEMs have several other advantages including the ability to estimate the direct effect, indirect effect, and total effect between variables, as well as the ability to investigate the reciprocal causal relationship between latent variables [40]. On the other hand, SEMs have been criticized for their limitations [41], for example the difficulty and errors that may occurs when attempting to interpret results, due to the complex modelling tasks SEMs entail and the need for large datasets for proper convergence.

SEMs have two components, a measurement model and a structural model. Specifically,

- 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 modelled, 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 [39].

The basic equation of the latent variable model is the following [42]:

$$H = B\,\eta + \Gamma\,\xi + \zeta \qquad (1)$$

in which: η (eta) is an $(m\times1)$ vector of the latent endogenous variables, ξ (xi) is an $(n\times1)$ vector of the latent exogenous variables, and ζ (zeta) is an $(m\times1)$ vector of random variables. The elements of the B (beta) and Γ (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 Γ matrix is an $(m\times n)$ coefficient matrix for the latent exogenous variables.

The basic equations of the measurement model are the following:

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

$$y = \Lambda y\eta + \varepsilon, \text{ for the endogenous variables} \qquad (3)$$

in which: x and δ (delta) are column q-vectors related to the observed exogenous variables and errors, respectively; Λx (lamda) is a $(q \times n)$ structural coefficient matrix for the effects of the latent exogenous variables on the observed variables; y and ε (epsilon) are column p-vectors related to the observed endogenous variables and errors, respectively; Λy is a $(p\times m)$ structural coefficient matrix for the effects of the latent endogenous variables on the observed ones [33].

Furthermore, a very useful tool for the interpretation of the results is path analysis, which was introduced by Wright [43] as a method for studying the direct and indirect effects of variables. 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.

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 due to the lack of consensus on which Goodness-of-Fit measures serve as “best” measures of model fit to empirical data [44]. Several research studies are implemented discussing these debates and a multitude of SEM Goodness-of-Fit methods [45]. 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 [42]. Values of the SRMR range between zero and one, with well-fitting models having values less than 0.08.

Finally, considering the large dataset from the driving simulator experiment, information regarding the data processing aim to conclude to the final database which was used for the statistical analyses. The driving at the simulator experiment data storage was performed automatically at the end of each experiment. The data was stored in text format (*.txt). The simulator records data at intervals of 33 to 50 milliseconds which means that each second measured value for each variable up to 30 times. It should be also mentioned that all the statistical analyses were implemented using the R statistical program, a language and environment for statistical computing and graphics.

3.6. Data acquisition

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. Table 1 presents the description, the minimum, maximum, and average value, per driving trial of each variable, giving a clear picture of the overall database that was used in the analysis.

Tab. 1: Database variable's characteristics

Driver characteristics	**Description**	**Min**	**Max**	**Mean**
Age	Age of the participant	22.00	78.00	44.47
Education	Years of education	0.00	16.00	12.00
Experience	Years of driving experience	3.00	50.00	23.06
Gender	Male/Female			
Driving error parameters	**Description**	**Min**	**Max**	**Mean**
Engine stops	How many times per trial, the engine of the vehicle stopped	0.00	11.00	1.05
Hit of side bars	How many times per trial, the vehicle hit the sidebars in the right	0.00	8.00	0.39
Outside road lines	How many times per trial, the vehicle crossed over road lines	0.00	2.00	0.01
Sudden brakes	How many times per trial, the driver braked suddenly	0.00	9.00	2.32
Speed limit violation	How many times per trial, the vehicle exceeded the speed limit	0.00	6.00	0.19
Slow rounds per minute	How many times per trial, the rounds per minutes of the motor were less than 1000	0.00	4.00	0.11
High rounds per minute	How many times per trial, the rounds per minutes of the motor exceeded 5000	0.00	13.00	0.34
Accident	How many times per trial an accident occurred	0.00	2.00	0.14
Driving performance parameters	**Description**	**Min**	**Max**	**Mean**
Time run	Duration (millisecond) since start of the drive	19.00	374.00	129.20
Distance car	Distance of the vehicle from the beginning of the drive (m)	99.67	3.104.35	1.176.48
Average speed	Actual speed (km/h)	19.63	69.83	39.24
Stdev average speed	Stdev of actual speed (km/h)	5.09	30.26	12.67
Reaction time	Reaction time at unexpected incident (millisecond)	500.00	5.484.00	1.493.00
Lateral position	Track of the vehicle from the middle of the road (m)	1.16	4.49	2.20
Std lateral position	Stdev of track of the vehicle from the middle of the road (m)	0.15	2.65	0.85
Average direction	Direction of the vehicle compared to the road direction (degrees)	0.01	4.03	1.93
Std average direction	Stdev of direction of the vehicle compared to the road direction (degrees)	0.00	3.13	1.93
Average brake	Brake pedal position (%)	0.00	7.07	1.87
Std average brake	Stdev brake pedal position (%)	0.00	25.06	12.01
Average gear	Chosen gear (0: idle; 6: reverse)	1.31	4.27	2.75

Std average gear	Stdev of chosen gear (0: idle; 6: reverse)	0.34	1.93	1.01
Average motor revolvation	Motor revolvation (1/min)	1.209.00	5.622.00	2.476.00
Std average motor revolvation	Motor revolvation (1/min)	273.70	1.795.10	676.70
Average space headway	Distance to the ahead driving vehicle (m)	18.76	927.52	206.03
Std average headway	Stdev of distance to the ahead driving vehicle (m)	13.35	434.22	97.60
Average timeheadway	Time to the ahead driving vehicle (sec)	3.54	256.84	37.10
Std Average timeheadway	Stdev of time to the ahead driving vehicle (sec)	6.61	1.169.97	198.70
Average time to line crossing	Time until the road border line is exceeded (sec)	17.69	552.93	130.72
Std average time to line crossing	Stdev of time until the road border line is exceeded (sec)	113.50	1.492.50	553.20
Average time to collision	Time to collision (all obstacles) (sec)	5.20	22.08	10.10
Std average time to collision	Stdev of time to collision (all obstacles) (sec)	1.54	10.80	5.40

4. Results

4.1. Structural Equation Modelling analysis

SEMs are developed for quantifying the effect of several risk factors including distraction sources, driver characteristics, road and traffic environment as well as driving error behavior on overall driving performance. In the first step, driving performance and driving error are defined as a new, unobserved variables, based on specific driving simulator measures while in the second step the effect of driving error behavior, distraction, driver, as well as road and traffic characteristics are estimated directly on this new driving performance variable (instead of being estimated on individual driving performance parameters).

Before proceeding to the core of the analysis, the definition of the new variables is provided:

- Driving performance: overall driving behavior based on individual driving parameters extracted from the simulator
- Driving error: any mental or physical activity, or failure to perform activity, that leads to either an undesired or unacceptable driving outcome [46]

The estimation results for both steps of the structural equation model are presented in Table 2.

Tab. 2: Estimation results of SEM

	Estimate	**Std Error**	**t value**	**P(>|z|)**	**Cronbach's a**
Driver Errors (Latent Variable 1)					
Hit of Side Bars	1.000	-	-	-	
Outside Road Lanes	0.547	0.214	2.559	0.010	
High Rounds Per Minute	0.950	0.276	3.436	0.001	
Driving Performance (Latent Variable 2)					
Average Speed	1.000	-	-	-	0.90
Stdev Lateral Position	-0.085	0.004	-23.117	0.000	0.91
Average Gear	0.049	0.002	22.043	0.000	0.92
Average Time to Line Crossing	-0.108	0.005	-20.114	0.000	0.93
Regression 1					
Driving Performance					
Driver Errors	-51.016	11.417	4.468	0.000	
Gender – Female	-16.739	3.799	-4.407	0.000	
Age	-2.244	0.681	-3.297	0.001	

	Estimate	Std Error	t value	P(>|z|)	Cronbach's a
Experience	2.103	0.694	3.031	0.002	
Regression 2					
Driving Errors					
Gender - Female	0.311	0.076	4.068	0.000	
Age	0.042	0.010	4.125	0.000	
Area - Urban	-0.300	0.068	-4.395	0.000	
Experience	-0.040	0.011	-3.815	0.000	
Education	0.004	0.001	3.174	0.002	
Summary statistics					
Minimum Function Test	608.01				
Degrees of freedom	40				
Goodness-of-Fit measure					
SRMR	0.088				

Results indicate that the latent variable, which reflects driving error is estimated based on the following variables:

- Outside Road Lanes refers to how many times per trial, the vehicle crossed over road lines
- High Rounds per Minute refers to how many times per trial, the rounds per minutes of the motor exceeded 5000
- Hit of Side Bars refers to how many times per trial, the vehicle hit the sidebars in the right

Moreover, the latent variable which reflects driving performance is estimated based on the following variables:

- Average speed refers to the mean speed, in km/hr
- Stdev Lateral position refers to the variability (standard deviation) of the lateral position of the vehicle
- Average Gear refers to the average chosen gear (0 = idle, 6 = reverse) of the simulator gear-box along the driving route
- Time to Line Crossing refers to the time until the road border line is exceeded, in seconds

In the lower part of Table 2, the overall model results are presented. The obtained value of SRMR (0.088) for this model is statistically accepted as it is slightly higher than the limit (<0.08) showing that the overall SEM is suitable. Furthermore, several other Goodness-of-Fit measures have been estimated including (RMSEA: 0.158, CFI: 0.793, TLI: 0.711).

The respective path diagram is presented in Figure 4. It is noted that green lines express a positive correlation 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.

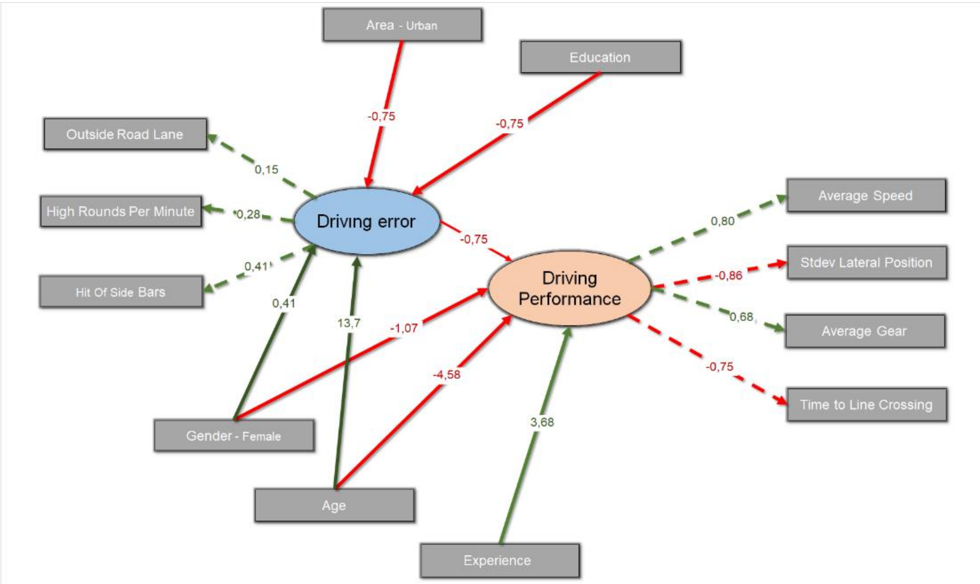

Fig. 4: Path diagram of driving error and driving performance SEM

4.2. Reliability analysis

Cronbach's a (alpha) is a coefficient of consistency that measures how well a set of variables or items measures a single, unidirectional latent construct [47]. Cronbach's alpha generally increases when the correlations between the items increase. Moreover, composite reliability is analogous to coefficient alpha, and reflects the internal consistency of the indicators measuring a given factor [48].

In the present study, Cronbach's alpha was applied to evaluate the internal consistency of the latent factor regarding driving performance as all the respective variables are continuous. The values of Cronbach's alpha of the observed variables as well as composite reliability of the latent variables are given in Table 2. A Cronbach's alpha of 0.7 or more indicates acceptable reliability [47, 48]. As shown in Table 2, the reliability of the scales is acceptable which implies that the methodological approach is valid.

5. Discussion

The proposed modeling framework entails some interesting and novel aspects. Firstly, with the use of Structural Equation Models, driving error and driving performance were jointly modelled as latent variables. Secondly, a set of indicators for estimating those latent variables was identified. Lastly, the relationship between those latent variables was quantified. With regards to driving performance, the most common driving performance categories include lateral control, longitudinal control, reaction time, gap acceptance, eye movement and workload measures. Results of the present work confirm the hypothesis that the selection of the specific measures that create overall performance should be guided by a rule of representativeness between the selected variables, as in the present structural equation model the unobserved driving performance is developed based on a longitudinal measure (speed), a lateral measure (standard deviation of the lateral position), a reaction time measure (the time until the road border line is exceeded) and the average gear.

A key outcome of the structural part of the model is the quantification of the correlation between driving errors and driving performance, as driving performance is negatively affected by driving errors. Furthermore, another interesting finding is that the overall driving performance is affected neither by road environment parameters such as type of road and traffic conditions nor by the distraction sources examined (cell phone use, conversation with a passenger). This is probably explained by the fact that the effect of these parameters is very weak compared to the effect of driving errors as well as of driver characteristics. In addition, another possible explanation is that the effect of road and traffic characteristics and distraction sources has been incorporated in the latent parameter of driving error behavior.

On the other hand, several driver characteristics are found to affect, together with driving errors, driving performance. More specifically, driver experience has a positive sign on driving performance indicating that an experienced driver performs much better than an unexperienced one in both driving environments and under both types of distraction. In addition, age and gender are the other two variables that have a significant effect on the statistical model. Females, as well as older drivers, seem to achieve worst driving performance compared to males and youngers ones respectively.

Regarding the effect of distraction on driving performance, conversation with the passenger was not found to have a statistically significant effect indicating that drivers do not change their driving performance while conversing with a passenger compared to undistracted driving. Considering that in the literature conversation with the passenger is supported either to affect [49] or not to affect [50, 51] specific driving measures, this finding highlights the importance of defining and investigating overall driving performance and not individual parameters. On the other hand, the effect of cell phone on driving performance is negative which is in line with the literature that cell phone use affects significantly individual driving performance parameters [52].

Concerning driving error behavior, 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 committing 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 indicates that both these driver characteristics help the driver properly handle a potentially hazardous situation and protect from committing an error.

6. Conclusions

The present research addressed two different objectives. The first was to investigate whether an unobserved driving performance and an unobserved driving error measures can be developed based on driving simulator data, while the second objective was to establish and quantify the effect of several risk factors including distraction sources, driver characteristics, road and traffic environment as well as driving error behavior on overall driving performance.

With focus on the first objective, model results indicate that structural equation models can be implemented on data based on, such a large driving simulator experiment, as both the respective Goodness-of-Fit measures and reliability analysis were statistically acceptable. Furthermore, considering that both driving performance, as well as driving error behavior are multidimensional parameters, the results of this analysis allow an important scientific step forward from simple unidimensional analyses to a sound combined analysis of the interrelationship between several risk factors, driving error and driving performance. The added value of the multidimensional aspect of the performed analysis is that both driving errors and driving performance are not estimated in terms of individual driving parameters, but as unobserved variables, which are influenced by several observed or unobserved factors.

With respect to the second objective, the relationship between the overall driving error behavior and the overall driving performance indicating was quantified - as initially suggested - and it was revealed that driving error is a critical factor that negatively affects driving performance. Although in the specific analysis the driving error is a latent variable, it has a significant effect on the estimation of driving performance indicating that driving errors determine at a high level the driving performance of the driver. Moreover, the effect of errors, while driving on the overall performance is so intense that eliminates the effect of several parameters including road and traffic conditions as well as distraction actions.

In spite of its strengths, the current study faced certain limitations which shall be considered while interpreting the main key-outputs of this research. The first concerns the methodological process. Both driving performance and driving error are multidimensional parameters which means that no single measure (neither driving performance nor driving error) can capture all aspects of these parameters. In each experimental process, many measures exist indicating that the decision regarding which measure or set of measures is used should be guided by the specific research question. However, most existing studies, individual driving performance measures are considered to represent driving performance and individual driving error parameters are considered to represent driving error behavior. Instead, unobserved (latent) new variables can be developed based on the collected driving simulator individual measures and represent with a statistical significance the overall driving performance and driving error behavior respectively. Another limitation concerns the statistical analysis methodologies implemented on driving simulator experiments investigating driving behavior parameters.

Based on the above, although the consideration of latent variables and the implementation of SEMs, is found to be useful and promising, allowing a new approach on the investigation of driving behavior, there are several conceptual and methodological considerations that deserve further research. The creation of latent (unobserved) variables, could be further developed and applied in more general driving behavior scientific fields and especially different experimental methods (on road, naturalistic experiments) that can provide more reliable data. Within this framework, 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.

Finally , it is important to highlight that due to paper size considerations, more sophisticated methods, such as Mixed-effects Ordered Probit model [53] or Linear Mixed model [54], had not taken into consideration; however, this kind of analyses should be definitely included in future work. It is evident that these statistical methods have the ability to handle the errors generated from repeated subject variable as the participants are exposed to all scenarios. Thus, a more comprehensive picture of the correlation between driving errors and driving performance could be drawn if a comparative analysis of the results delivered from different statistical methods was occurred.

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