Can structural equation models assess overall driving performance in driving simulator experiments?

Panagiotis Papantoniou[1], George Yannis[2], Constantinos Antoniou[1], Dimosthenis Pavlou[2]

[1]Chair of Transportation Systems Engineering, Technical University of Munich
Arcisstrasse 21, D-80333, Munich, Germany, p.papantoniou@tum.de
[2]Department of Transportation Planning and Engineering, National Technical University of Athens
5 Heroon Polytechniou str., GR-15773, Athens, Greece

Abstract

Structural equation models (SEM) belong to latent model analysis. This type of analysis is used to deal with several difficult modelling challenges, including cases in which some variables of interest are unobservable or latent and are measured using one or more exogenous variables. The objective of the present research is to investigate whether the case of the unobserved driving performance can be assessed through this type of analysis. For this purpose, a large driving simulator experiment was carried out, in which 95 participants from all age groups were asked to drive under different types of distraction (no distraction, conversation with passenger, mobile phone use) in rural/urban road environment, in low/high traffic. Data collected from the driving simulator experiment include 16 continuous driving performance parameters such as longitudinal control measures (mean speed, headways, etc.), lateral control measures (lateral position, standard deviation of lateral position etc.), the reaction time of the driver at unexpected incidents and other driving performance parameters. Then, in the framework of the statistical analyses, latent analysis is implemented, including 2 structural equation models, in which the latent variable reflects the unobserved driving performance of the participants, and is based on several driving performance parameters. Moreover, in the structural part of the model the effect of several variables includes distraction sources, area type (urban/rural area), traffic conditions (low/high traffic) and driver characteristics (age, gender, driving experience) on driving performance is estimated. Results indicate that the selection of the specific measures that define overall performance should be guided by a rule of representativeness between the selected variables, as in the present structural equation models the unobserved driving performance are defined based on a longitudinal measure, a lateral measure and a time related measure.

Keywords

Driving performance, driving simulator, latent analysis, structural equation model

1. Introduction

Approximately 1.25 million people die every year on the world's roads, and another 20 to 50 million sustain nonfatal injuries as a result of road traffic accidents. These injuries and fatalities have an immeasurable impact on the families affected, whose lives are often changed irrevocably by these tragedies, and on the communities in which these people lived and worked [1]. Within this framework, road accidents are estimated to be the eighth leading cause of fatalities globally, with an impact similar to that caused by many communicable diseases [2] and the leading cause of fatalities for young people aged 15–29 years [3]. Despite the fact that road traffic casualties presented a constantly decreasing trend during the last years, the number of fatalities in road accidents in several countries is still unacceptable and illustrates the need for even greater efforts with respect to better driver behaviour and increased road safety [4].

Human factors are the basic causes in 65-95% of road accidents [5]. The remaining factors include road environment (road design, road signs, pavement, weather conditions etc.) and vehicle characteristics (equipment and maintenance, advanced assistance systems, damage etc.), as well as combinations of these three contributory factors. Based on the above, human factors research examines the way people interact with various aspects of the world and aims to make these interactions safer, healthier, and more efficient. This interdisciplinary field of research has a wide scope of application, spanning road safety, healthcare delivery, physical, cognitive, and technological systems. In the context of safety features and road safety, human factors research aims to understand the driver's role in the safe operation of his or her vehicle.

Focusing on driver behaviour, the most crucial parameters on road safety until the era of autonomous vehicles will prevail, respective research often makes 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. Driving simulators, however, vary substantially in their characteristics, and this can affect their realism and the validity of the results obtained. Despite these limitations, driving simulators are an increasingly popular tool for measuring and analyzing driving performance, driver distraction etc., and numerous studies have been conducted, particularly in the last decade [6].

Consequently, driving performance is a multidimensional phenomenon which means that no single driving performance parameter can capture all aspects of the overall driving performance. The large number of parameters that are estimated in each experimental process indicates that the decision regarding which parameter or set of parameters is used should be guided by the specific research question. The parameters for assessing driving performance vary significantly, and the driving-related outcomes have been analysed in several studies as presented below: speed [7], lane position [8, 9], accident probability [10], number of eye glances [9], headway [11], reaction time [12]. Certainly, a more holistic approach would be beneficial, whereby many independent variables used in concert will describe the overall performance capturing the effect of many variables together with their interrelationships

Latent model analysis and more specifically structural equation models have been rarely being implemented in the field of driving behaviour. Structural equation models have been previously applied to many areas of transportation including transit system quality of service analysis [13], travel behavior modelling [14], mode choice modelling [15], driver behavior modelling [16] and public acceptability analysis of new technologies for traffic management [17] SEM models 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 [13].

Based on the above, the objective of the present research is to investigate whether unobserved overall driving performance can be assessed through structural equation models based on driving simulator data. In the next chapter, the methodological approach is presented including the overview of the experiment, sample characteristics and analysis method. Then the development of an advanced statistical analysis methodology which consists two structural equation models is presented. Finally, the results of the study are discussed, and future work is outlined.

2. Methodology

1.1. Overview of the experiment

Within this framework of the present research, a driving simulator experiment was carried out, in which 95 participants were asked to drive under different types of distraction (no distraction, conversation with passenger, cell phone use) in different road (urban/rural) and traffic conditions (high/low). Each participant aimed to complete 12 driving trials, while in each trial, 2 unexpected incidents were scheduled to occur at fixed points along the drive. Participants were also asked to fill in two questionnaires regarding their driving behaviour, as well as self-assessment and memory tests. The above stages were designed based on specific parameters and criteria as well as design principles that were appropriate for the research assumptions and objectives of the research.

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 is located. The NTUA driving simulator is a motion base quarter-cab and consists of 3 LCD wide screens 40" (full HD: 1920x1080pixels), driving position and support motion base. The dimensions at a full development are 230x180cm, while the base width is 78cm and the total field of view is 170 degrees (Figure 1).


Figure 1. Driving simulator

1.2. Driving at the simulator

The driving simulator experiment started with a practice drive (approximately 10 minutes), until the participant fully familiarized with the simulation environment. A familiarization session or “practice drive” is typically the first step of all simulator experiments. The driving simulator provided a “Free Driving” scenario that familiarizes the participants with the demands of an everyday drive. The greater part of the drive was designed in an inter-urban environment, but there was also a short crossing through a small city with traffic signals and junctions. 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 the above-mentioned criteria were satisfied (based on the coordinator researcher who was assisting and evaluating the participant during their familiarization drive), the participant moved on to the next phase of the experiment. It should be highlighted that there was no exact time restriction within this procedure.

Afterwards, the participant drove the two sessions (~20 minutes each). Each session corresponded to a different road environment:

- A rural route that was 2.1 km long, single carriageway and the lane width was 3m, with zero gradient and mild horizontal curves.
- An urban route that was 1,7km long, at its bigger part dual carriageway, separated by guardrails, and the lane width was 3.5m. Moreover, narrow sidewalks, commercial uses and parking were available at the roadsides.

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

The traffic scenarios were:

- QL: Moderate traffic conditions – with ambient vehicles’ arrivals drawn from a Gamma distribution with mean m=12 sec, and variance σ^2=6 sec, corresponding to an average traffic volume Q=300 vehicles/hour.
- QH: High traffic conditions – with ambient vehicles’ arrivals drawn from a Gamma distribution with mean m=6 sec, and variance σ^2=3 sec, corresponding to an average traffic volume of Q=600 vehicles/hour.

Consequently, in total, each environment (urban / rural) included six trials, i.e. six drives of the simulated route. During each trial of the experiment, 2 unexpected incidents were scheduled to occur at fixed points along the drive (but not at the exact same point in all trials, in order to minimize learning effects). More specifically, incidents in rural area concerned the sudden appearance of an animal (deer or donkey) on the roadway, and incidents in urban areas concerned the sudden appearance of an adult pedestrian or of a child chasing a ball on the roadway (Figure 2). The experiment was counterbalanced concerning the number and the order of the trials, on the basis of several combinations of the parameters of interest

Figure 2. Unexpected incident - donkey crossing the lane / child with ball crossing the road

1.3. Sample characteristics

In Table 1 the distribution of participants per age and gender is presented. 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 and age groups.

Table 1. Distribution of participants per age group and gender

Age group	Female		Male		Total	
18-34	9	19%	19	40%	28	29%
35-55	19	40%	12	26%	31	33%
55+	20	42%	16	34%	36	38%
Total	48	100%	47	100%	95	100%

In general, each experiment is based on a combination of conditions, resulting from the combinations of levels of the variables of interest. The complete combination of all levels of the variables of interest results in a full factorial design. To achieve the above objectives and to collect the data for the analysis a full-factorial driving simulator experiment was designed in which participants drove in 2 levels of environment (urban, rural) x 2 levels of traffic (QL, QH) x 3 levels of distraction, for a total of 12 experimental conditions.

1.4. Analysis Method

Structural equation models belong to latent model analysis and represent a natural extension of a measurement model, and a mature statistical modelling framework. The SEM is a tool developed largely by clinical sociologists and psychologists. It is designed to deal with several difficult modelling challenges, including cases in which some variables of interest to a researcher are unobservable or latent and are measured using one or more exogenous variables, endogeneity among variables, and complex underlying social phenomena [18]. In the present research, the case of the unobserved overall driving performance is attempted to be investigated through this type of analysis.

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 [18].

The basic equation of the latent variable model is the following [19]:

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

in which η (eta) is an ($m \times 1$) vector of the latent endogenous variables, ξ (xi) is an ($n \times 1$) vector of the latent exogenous variables, and ζ (zeta) is an ($m \times 1$) 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:

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

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

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.

Model Goodness-of-Fit measures are an important part of any statistical model assessment. GOF measures in SEMs are an unsettled topic, primarily as a result of lack of consensus on which GOF measures serve as "best" measures of model fit to empirical data [20]. Several researches are implemented discussing these debates and a multitude of SEM GOF methods [20, 21, 22, 23]. The first class of GOF indices includes measures of parsimony. Models with few parameters are preferred to models with many parameters, providing that the important underlying model assumptions are not violated. This modeling philosophy is born by a general desire to explain complex phenomena with as simple a model as possible. Another class of fit measures is based on the population discrepancy. These measures rely on the notion of a population discrepancy function (as opposed to the sample discrepancy function) to estimate GOF measures, including the noncentrality parameter (NCP), the root mean square error of approximation (RMSEA), and PCLOSE, the p-value associated with a hypothesis test of RMSEA ≤ 0.05. For details on these measures the reader should consult Steiger et al. [23] Other GOF measures in this category include the relative fit index (RFI), the incremental fit index (IFI), the Tucker-Lewis coefficient, and the comparative fit index (CFI), discussion on which is found in Bollen [24], Bentler [25] and Arbuckle and Wothke [20]. Finally, 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 [19]. Values of the SRMR range between zero and one, with well-fitting models having values less than 0.08.

3. Analysis and Results

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. The final master file, which was extracted in both .xls and .csv formats, included in total 95 rows x 863 columns ((95 participants) x (7 general information variables + 535 driving at the simulator variables + 321 questionnaire variables). 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.

Table 2: Driving Simulator Variables

	Variables	Description
1	Time	current real-time in milliseconds since start of the drive.
2	x-pos	x-position of the vehicle in m.
3	y-pos	y-position of the vehicle in m.
4	z-pos	z-position of the vehicle in m.
5	road	road number of the vehicle in [int].
6	richt	direction of the vehicle on the road in [BOOL] (0/1).
7	rdist	distance of the vehicle from the beginning of the drive in m.
8	rspur	track of the vehicle from the middle of the road in m.
9	ralpha	direction of the vehicle compared to the road direction in degrees.
10	Dist	driven course in meters since begin of the drive.

11	Speed	actual speed in km/h.
12	Brk	brake pedal position in percent.
13	Acc	gas pedal position in percent.
14	Clutch	clutch pedal position in percent.
15	Gear	chosen gear (0 = idle, 6 = reverse).
16	RPM	motor revolvation in 1/min.
17	HWay	headway, distance to the ahead driving vehicle in m.
18	DLeft	distance to the left road board in meter.
19	DRight	distance to the right road board in meter.
20	Wheel	steering wheel position in degrees.
21	THead	time to headway, i. e. to collision with the ahead driving vehicle, in seconds.
22	TTL	time to line crossing, time until the road border line is exceeded, in seconds.
23	TTC	time to collision (all obstacles), in seconds.

Proceeding to the core of the statistical analysis the objective of the research should be recalled. The target is to estimate the effect of several factors directly on the overall driving performance. For this purpose, through the implementation of latent model analysis, in the first step driving performance is defined as a new, unobserved variable, based on specific driving simulator parameters while in the second step the effect of 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).

Table 3 Estimation results of the driving performance SEM

	Est.	**Std.err**	**t value.**	**P(>|z|)**
Latent Variable				
Driving Performance				
Average Speed	1.000	-	-	-
Stdev Lateral Position	0.128	0.042	3.047	0.002
Average Gear	0.061	0.005	12.870	0.000
Time to Line Crossing	-0.320	0.135	-2.374	0.018
Regression				
Driving Performance				
Gender - Female	-3.645	0.688	-5.457	0.000
Age - Old	-6.766	1.070	-6.323	0.000
Traffic - Low	4.389	0.661	6.644	0.000
Distraction – Mobile	-3.390	0.788	-4.300	0.000
Education	-0.610	0.110	-5.755	0.000
Summary statistics				
Minimum Function Test	271.08			
Degrees of freedom	17			
Goodness-of-fit measure				
SRMR	0.070			

Regarding the assessment of the statistical model, the value of SRMR is used. It is noted that values of the SRMR range between zero and one, with well-fitting models having values less than 0.08. Considering that the obtained value of SRMR in the present model is 0.07, the overall statistical models is accepted.

The respective path diagram (extracted from R statistical tool) is presented in Figure 3. 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.

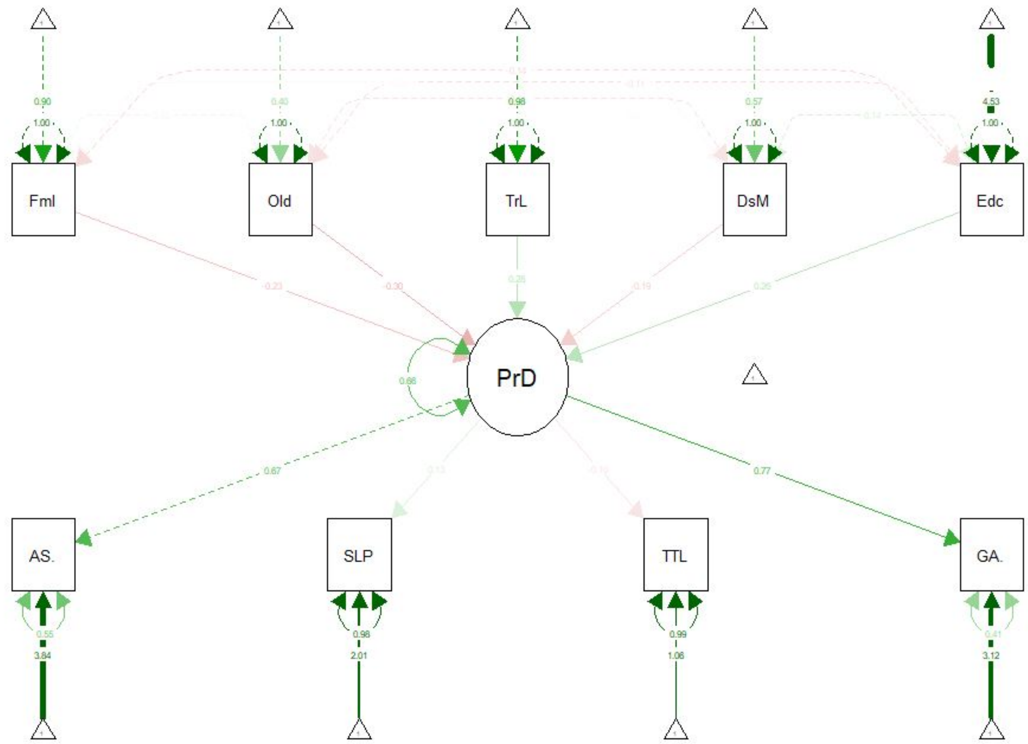

Figure 3. Path diagram of the driving performance SEM

In the structural model of the overall SEM, the new driving performance variable is the dependent while the statistically significant independent variables include cell phone use, area type, traffic conditions as well as several driver characteristics (age, gender, driving experience).

A first methodological finding is that from the 23 examined driving simulator parameters, only 4 participate in the development of the new unobserved driving performance behaviour including a longitudinal (speed), a lateral (standard deviation of the lateral position) the average gear and the time until the road border line is exceeded.

In the next step, a second model is presented investigating the difference of overall driving performance before and after an unexpected incident. For this purpose, the average value of all driving performance measures was estimated for a time period of 30 seconds before and 30 seconds after the event. Then a new model has been developed aiming to quantify the effect of distraction, driver as well as road and traffic characteristics directly on the difference of driving performance due to an unexpected event.

Table 4 Estimation results of the different driving performance SEM

	Est.	Std.err	t value.	P(>|z|)
Latent Variable				
Dif Driving Performance				
Dif Average Speed	1.000	-	-	-
Dif Stdev Lateral Position	0.003	0.001	3.016	0.003
Dif Rpm	29.225	7.542	3.875	0.000
Regressions				
Dif Driving Performance				
Distraction – Cell phone	-1.075	0.768	-1.399	0.162
Distraction – Passenger	-1.303	0.624	-2.090	0.037
Traffic - Low	-3.156	0.554	-5.700	0.000
Age - Old	1.425	0.767	1.858	0.063
Summary statistics				
Minimum Function Test	26.22			
Degrees of freedom	8			
Goodness-of-fit measure				
SRMR	0.027			

Regarding the assessment of the statistical model, the value of SRMR is used again. Considering that the obtained value of SRMR in the present model is 0.027, the overall statistical models is accepted. The respective path diagram is also presented in Figure 4 as being extracted from the statistical programme.

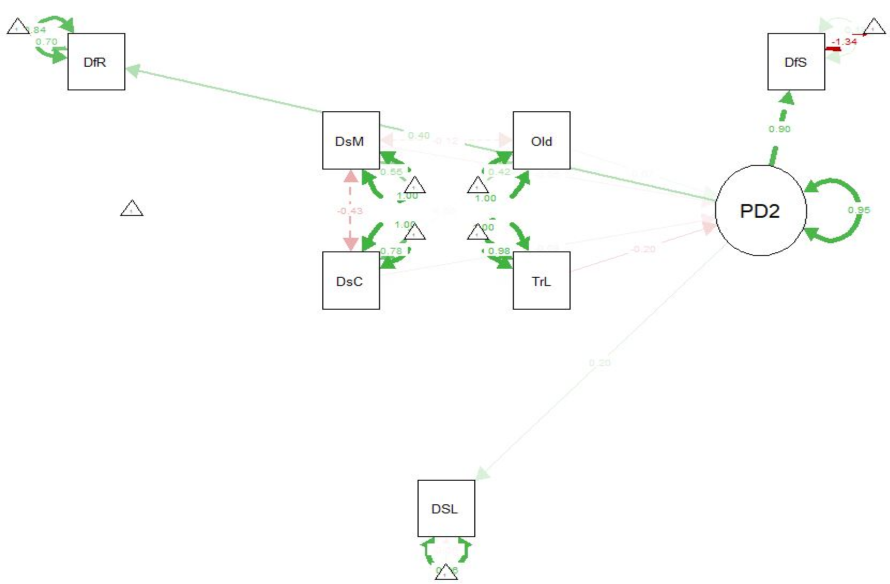

Figure 4. Path diagram of the different driving performance SEM

A key methodological finding is that from the 23 examined driving simulator parameters, only 3 participate in the development of the new unobserved driving performance behaviour including a longitudinal (difference on speed), a lateral (difference on standard deviation of the lateral position) and the difference in motor revolvation on the vehicle.

4. Discussion

The objective of the present research is to investigate whether unobserved overall driving performance can be assessed through structural equation models based on driving simulator data. If this was confirmed, the second objective was to quantify the effect of several risk factors including distraction sources, driver characteristics, road and traffic environment on the overall driving performance and not in independent driving performance measures.

Regarding the first objective, considering that driving performance is a multidimensional phaenomenon, the results of this analysis allow an important scientific step forward from piecemeal analyses to a sound combined analysis of the interrelationship between several risk factors (including driver distraction) and driving performance. Within the framework of the present research, through the first model, driving performance is estimated as an unobserved variable defined by four different driving simulator parameters (speed, standard deviation of the lateral position, average gear and time until the road border line is exceeded) which capture a statistical significant part of overall performance. Consequently, based on the second model, the difference in driving performance after an unexpected event is defined by three diving simulator parameters i.e. difference of average speed, difference of lateral position variability and difference of motor revolvation. Based on the above, the goodness of fit measures of the above presented model confirm the initial hypothesis that driving performance can me estimated through latent model analysis and more specifically through structural equation models is con. More specifically, results of the present research indicate that the selection of the specific measures that define overall performance should be guided by a rule of representativeness between the selected variables.

In addition, the structural part of both models indicates which risk factors affect unobserved driving performance and unobserved difference in driving performance. More specifically, three factors appear in both models i.e the use of cell phone while driving, older drivers and low traffic conditions. Focusing on the model of overall driving performance, results indicate that conversation with the passenger was not found to have a statistically significant effect indicating that drivers do not change their performance while conversing with a passenger compared to undistracted driving. On the other hand, that cell phone use has a negative effect on driving performance. Furthermore, regarding driver characteristics, both age, gender and education have a significant effect on driving performance indicating that driver-related characteristics play the most crucial role in overall driving performance. Examining the difference of driving performance after an unexpected event, both examined distraction factors were found to negatively affect the latent variable indicating that while conversing with the passenger or talking on the cell phone during an unexpected event, driving performance is less affected after the event. On the other hand, older drivers were found to change more their driving performance due to an unexpected event especially in low traffic conditions.

Finally, the application of this methodology revealed a number of open issues for further research in the inter-disciplinary field of driving behaviour. Firstly, the present methodological approach could be further developed and applied in more general driving behaviour scientific fields. 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. In addition, several other latent variables can be created and examined, depending on the experimental database and the specific research questions.

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