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IDENTIFICATION AND ANALYSIS OF CONTRIBUTING FACTORS RELATED TO ROAD CRASHES

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**IDENTIFICATION AND ANALYSIS OF CONTRIBUTING
FACTORS RELATED TO ROAD CRASHES**

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ABSTRACT

Safety is a central point when considering road infrastructure management, and also plays a critical strategic role in a nation's development. However, high rates of fatal crashes and severe injuries are still an unreasonable cost that many countries pay for transport mobility. This scenario is even more disproportionate when looking at figures from developing countries. Recognizably, there is a share of randomness in crash occurrences, but there are also identifiable contributing factors to that equation. Hence, a more mature road safety strategy claims a holistic perspective that considers all factors involved. This study advocates a proactive approach that considers human-road interaction to identify risky conditions that can trigger operational and driving mistakes connected to crashes, based on the idea that human characteristics influence road perception and road environment influences driver behavior. Therefore, this thesis focuses on driver-road interaction, ultimately tested in a driving simulator experiment, examining the impact of the driver profile and road countermeasures on drivers' performance. The simulated scenario was defined through a Clustering Analysis method taking advantage of crash records, traffic counts, and road inventory data. The scenario consists of a non-challenging single-lane rural highway connected to single-vehicle crashes. The driver profile was incorporated in the analysis through the driver's behavioral history measured by a new and validated version of the Driver Behavior Questionnaire (DBQ), a traditional tool in road safety research adapted to the scenario of interest and target population of this research. The relationship between DBQ and crash involvement was explored using a random-parameters model, which indicated that driver profile, translated into DBQ scores, had a heterogeneous effect on the probability of crashes. The driving simulator experiment followed the best practices from driving simulator studies and tested three low-cost countermeasure schemes: side poles on curves and peripheral lines in two locations (before and after curves). Random-parameters models with heterogeneity in the means, accounting for the unobserved individual- and countermeasure-specific heterogeneity, were used to model the relationship between drivers' performance (speed and trajectory) and driver profile, countermeasures, and the interaction between both. The results indicated that the Ordinary Violation (OV) scores explained a considerable part of the heterogeneity found in drivers' performances, supporting the DBQ as a tool for measuring driving performance. The heterogeneity in the means caused by OV and Errors (E) scores in the presence of peripheral lines suggested a difference in how drivers react to the countermeasures based on their profiles. Peripheral lines made high E scores drivers correct their trajectory to the center of the lane, and speed reduction effects were greater for drivers with high OV. This study revealed that drivers altered their behavior in response to the countermeasures, including those drivers believed to violate safe driving practices deliberately. Peripheral lines were more efficient to moderate speed but did not positively influence drivers' trajectory. Although the design of the peripheral lines used in this research still needs improvement, it represents an alternative to change driver behavior in a non-challenging or monotonous road environment, potentially avoiding trigger factors to crashes such as fatigue and speeding.

KEYWORDS: Crash Analysis, Driver Behavior, Road-driver Interaction, Road Safety

RESUMO

A segurança é um ponto central quando se considera a gestão da infraestrutura viária, também desempenhando um papel estratégico crítico no desenvolvimento de uma nação. No entanto, as altas taxas de acidentes fatais e lesões graves ainda são um custo desastroso que muitos países pagam pela mobilidade de transportes. Esse cenário é ainda mais desproporcional quando se olha para os números de países em desenvolvimento. Reconhecidamente, há uma parcela de aleatoriedade na ocorrência de acidentes, mas também existem fatores identificáveis que contribuem nesta equação. Assim, uma estratégia de segurança viária mais madura exige uma perspectiva holística que considere todos os fatores envolvidos. Este estudo defende uma abordagem proativa que considere a interação humano-via para identificar as condições de risco que podem desencadear erros operacionais e de condução relacionados à ocorrência de acidentes, tendo como base a ideia de que as características humanas influenciam a percepção da via e o ambiente viário influencia o comportamento do condutor. Sendo assim, esta tese se concentra na interação condutor-via, por fim testada em um ensaio com simulador de condução, examinando o impacto do perfil do condutor e de contramedidas viárias no desempenho dos condutores. O cenário simulado foi definido por meio de um método de Análise de Agrupamento (*clustering*) com base nos registros de acidentes, contagens de tráfego e dados do inventário da via. O cenário consiste em uma via rural de pista única e traçado pouco desafiador associada a acidentes de um único veículo. O perfil do condutor foi incorporado na análise por meio do histórico comportamental do condutor através de uma versão nova e validada do *Driver Behavior Questionnaire* (DBQ), uma ferramenta tradicional em pesquisas de segurança viária, adaptada ao cenário de interesse e população-alvo desta pesquisa. A relação entre o DBQ e o envolvimento em acidentes foi explorada por meio de um modelo de parâmetros aleatórios (*random parameters*), que indicou que o perfil do condutor, traduzido em escores do DBQ, tem um efeito heterogêneo na probabilidade de ocorrência de acidentes. O ensaio do simulador de condução seguiu as melhores práticas advindas de estudos de simulador de condução e testou três esquemas de contramedidas de baixo custo: postes laterais nas curvas e linhas periféricas em dois locais (antes e depois das curvas). Modelos de parâmetros aleatórios com heterogeneidade nas médias, levando em consideração a heterogeneidade não observada com relação aos indivíduos e às contramedidas, foram usados para modelar a relação entre o desempenho dos condutores (velocidade e trajetória) e o perfil do condutor, as contramedidas e a interação entre ambos. Os resultados indicaram que os escores de Violação Ordinária (VO) explicaram parte considerável da heterogeneidade encontrada no desempenho dos condutores, ratificando o DBQ como uma ferramenta para medir o desempenho dos condutores. A heterogeneidade nas médias causadas pelos escores de VO e Erros (E) na presença das linhas periféricas indicou uma diferença na forma como os condutores reagem às contramedidas com base em seus perfis. As linhas periféricas fizeram com que os condutores com escores E altos corrigissem sua trajetória para o centro da via, já os efeitos de redução da velocidade foram maiores para os condutores com VO alto. Este estudo revelou que os condutores alteraram seu comportamento em resposta às contramedidas, incluindo os condutores que, acredita-se, violam deliberadamente as práticas de condução segura. As linhas periféricas foram mais eficientes para moderar a velocidade, mas não influenciaram positivamente a trajetória dos condutores. Embora o desenho das linhas periféricas utilizado neste estudo ainda precise de melhorias, ele representa uma alternativa para alterar o comportamento do condutor em um ambiente rodoviário não desafiador ou monótono, evitando fatores desencadeadores de acidentes como fadiga e excesso de velocidade.

PALAVRAS-CHAVE: Análise de Acidentes, Comportamento do Condutor, Interação Condutor-via, Segurança Viária

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1

INTRODUCTION

1.1. MOTIVATION AND CORNERSTONES

The Vision Zero policy implemented in Sweden at the beginning of the millennium, aiming to achieve a target of zero fatal crashes and severe injuries, introduced a holistic perspective on road safety. Before its widespread, the tradition towards crash occurrences was blaming individuals at the sharp end for taking unsafe acts. Reason (2008) called this earlier philosophy of error management the *Person Approach*, as opposed to what has become known worldwide as the *Safe System Approach*.

The adoption of the Safe System Approach strategy, captained by countries such as Sweden, The Netherlands, and Australia, successfully reduced the number of fatal crashes and severe injuries in many countries that implemented it. These results led international road safety institutions, such as the World Health Organization (WHO), the Global Road Safety Facility (GRSF), the International Road Federation (IRF), the International Transport Forum (ITF – OCDE), the Road Assessment Programme (iRAP), and the PIARC World Road Association, to endorse this policy in order to enhance traffic system in general and achieve road safety targets (Bliss and Breen, 2013; Herod, 2022; International Road Federation, 2021; International Transport Forum, 2022; ITF, 2016; PIARC, 2019a; Welle et al., 2018; WHO, 2018).

Nevertheless, the focus and major achievements of the Safe System were made in mainly one field: road infrastructure (Wegman et al., 2008). In the last years, traffic fatalities figures have stagnated in countries where the Safe System Approach was actively adopted, indicating that it becomes harder to make further improvements after reaching a certain level of safety (WHO, 2018). Therefore, the attention turns to the human factor again, only now focused on the road-human interaction.

Recognizably there is a share of randomness in crash occurrence, and, eventually, there would be a limit for the number of preventable outcomes due to collisions. However, considering the multifactorial nature of crashes, there is still room for improvements in driver-road interaction, a yet overlooked topic. For instance, if high-crash locations indicate contributing parameters characterized by the road itself (Krebs and Kloeckner, 1977 apud Lamm et al., 2002), on the other hand, some studies pointed out that crash and near-crash involvement was somewhat persistent over time for individual drivers and hence, to some extent, predictable based on enduring personal factors (Dorn and af Wåhlberg, 2021; Engström et al., 2019).

In this context, PIARC published the Road Safety Evaluation Based on Human Factors Method, which presents the principles of Human Factors steering the interaction between the driver, the road infrastructure, and its surroundings. It consists of a proactive approach that looks at the probability of a wrong man-road interaction to identify road deficiencies that can trigger operational and driving mistakes that, if not timely corrected, bring the occurrence of a crash (PIARC, 2019b).

Far from being a concept only suitable for countries with higher road safety levels, this concept can be included in the road safety strategy of developing countries that already have some degree of road

infrastructure but still struggle with fatality rates overall. The World Health Organization (WHO, 2018) has already highlighted that 90% of road traffic deaths occur in low- and middle-income countries; therefore, the transferability of strategies to their context is essential to achieving the target of preventing at least 50% of road traffic deaths and injuries by 2030 set by the new Decade of Action for Road Safety (United Nations General Assembly, 2020).

The thesis is based on the idea that driver perception of the road environment affects driver behaviors and, thus, the risk of crashes. The driver's behavior is not always the primary cause of a crash, but its positive or negative contribution is always present, translated into interaction with the road environment, other road users, and vehicle control tasks. Research in this area calls for a multidisciplinary perspective, involving aspects of engineering and psychology; however, the existing literature has not yet adequately contemplated a comprehensive assessment of road-driver interaction.

Therefore, this work aims to provide a comprehensive analysis focusing on road-driver interaction, considering driver profile and crash characteristics, which was subjected to an examination of driver performance in a driving simulator – a powerful research tool that allows studies to manipulate confounding variables, reproduce repetitively identical situations for each participant, and simulate risky situations without engaging drivers in dangerous activities – not disregarding the role of the road environment, but using it in favor of a safer traffic system, to contribute to this branch of knowledge on the theoretical and practical levels and support road safety strategies to create a safer environment for all.

1.2. RESEARCH QUESTIONS AND OBJECTIVES

Road safety should be a core responsibility of road agencies, and this document aims to contribute to road safety knowledge, especially on rural highways. This work aligns with a holistic perspective of road safety, focusing on road-driver interaction, where human characteristics influence road perception and road environment influences driver behavior (PIARC, 2016).

This research is intended to act on two levels with different contributions:

- i. At a theoretical level: to contribute to the body of knowledge regarding the relative importance of drivers' characteristics and road environment on driver performance with a comprehensive analysis also developing novel research methods and models that can be reproduced in other contexts;
- ii. At a practical level: to support road administrators with feasible safety measure alternatives towards potential crash risk conditions still not fully addressed in standard manuals, acknowledging the interaction between drivers and the road environment.

The main premise of this thesis is that road-driver interaction is a crucial factor in crash occurrences and investigating the dynamics involved in this relationship is the first step to identifying and solving safety problems. Furthermore, considering that changes in the road environment can influence driver behavior, it is possible to take advantage of this interaction to encourage safe driving behavior. Therefore, the questions this research aims to answer are:

- RQ 1.** How is the road-driver interaction being studied by experiments with driving simulators, and how do their findings relate to road safety literature gaps?
- RQ 2.** How to identify potential risky conditions considering crash data for a driving simulator experiment, reaching a balance between diversity and specificity?
- RQ 3.** How to measure drivers' profiles considering this thesis' subpopulation and scenario of interests?

- RQ 4.** How are the drivers' profiles and crash occurrences related?
- RQ 5.** To what extent do drivers' profiles influence driver performance?
- RQ 6.** Do drivers respond differently in terms of performance to road environment changes based on their profiles?

1.3. RESEARCH DEVELOPMENT AND METHODOLOGIES

The thesis was developed in the format of scientific papers already published or submitted to peer-reviewed journals of high interest for the research scope. **Figure 1.1** shows the correspondence between each research question and the paper where they are addressed. **Figure 1.1** also shows the connection of the direct contribution from each paper to the other.

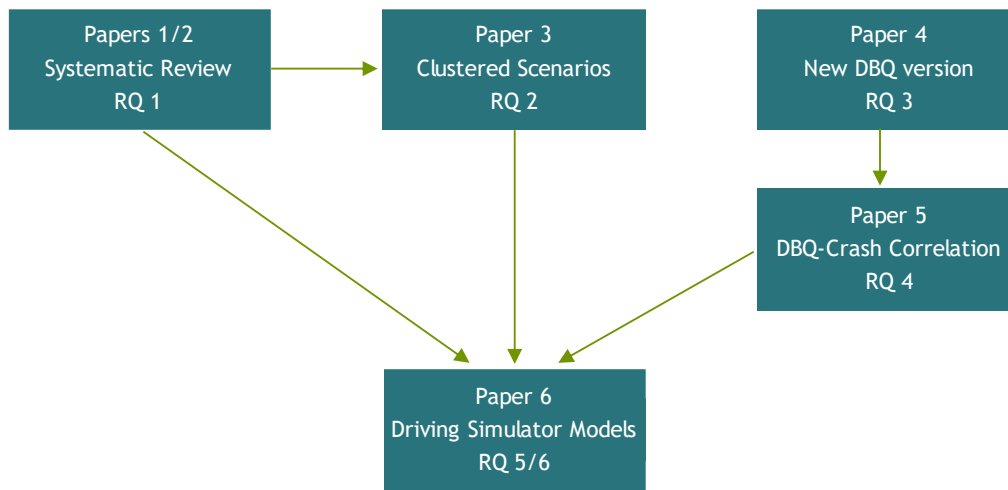


Figure 1.1: Mapping of papers development and thesis research questions addressed

In order to answer the research questions, different methodologies were applied. In short, to address RQ1, a systematic review of the literature was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. The PRISMA guideline is a recognizable method consisting of an evidence-based minimum set of items for reporting in systematic reviews and meta-analyses to guarantee the completeness of reporting.

RQ2 was addressed in a proposed approach based on Clustering Analysis, a method intended to classify cases into similar significant groups based on their variables' categories. The partitional clustering K-medoids was chosen to deal with the categorical and numeric variables, typically the case of traffic crash data, which were used as input to identify potential risk scenarios for the driving simulator experiment.

The primary method applied to elucidate RQ3 was Nonlinear Principal Component Analysis (NLPCA). NLPCA was considered an ideal approach to deal with quantitative data and nonlinear relationships, particularly useful for ordinal data such as the Likert Scale outputs from the driver behavioral history questionnaires distributed to participants in the research.

The relationship between drivers' profiles and crash occurrences of RQ4 was examined using a binary logit random-parameters model. The binary model was justified since only a few drivers were involved in more than one crash, meeting the discrete choice nature of the data. Furthermore, a random parameter approach was applied to allow estimated parameters to vary across observations to account for potential heterogeneity within the data, which was expected considering the multifactorial causes of crashes and the inclusion of variables describing behavior.

Research questions RQ5 and RQ6 were tackled through a driving simulator experiment considering different road scenarios. Results in terms of driving performance were analyzed together with driver profile data using a random parameter regression model with heterogeneity in the means to accommodate not only the potential heterogeneity within the data but also the nature of the performance measures (continuous variables) and the panel data structure (repeated measurements).

All the methodologies adopted are further explained in their respective paper. The six scientific papers are presented in six chapters (Chapters 2-7), and the thesis structure is detailed in **Section 1.5**.

1.4. DATABASES

This thesis used five primary data sources as input in different stages of the research (see **Figure 1.2**): (i) road inventory; (ii) crash data; (iii) traffic counts; (iv) online surveys; and (v) driving simulator. The last two databases were constructed within the scope of the thesis; however, the first three were drawn from external data sources and, thus, described in the following subsections.

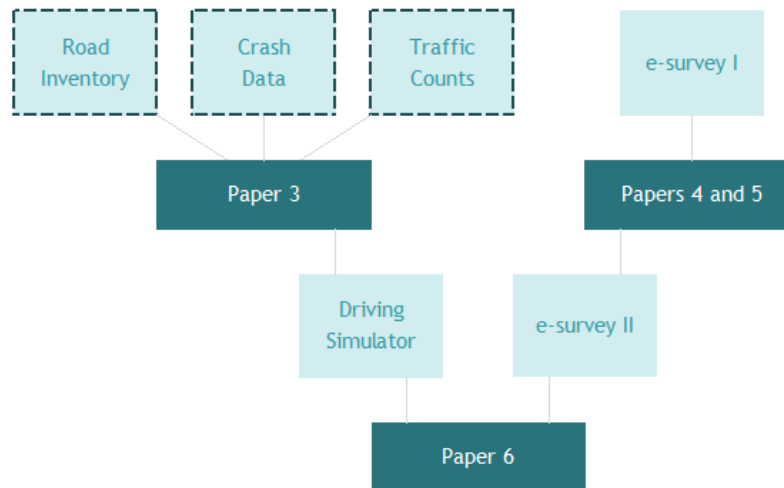


Figure 1.2: Main databases used as input for the papers

1.4.1. ROAD INVENTORY

Data from three segments of two-lane (one lane in each direction) rural highways located in the Rio Grande do Sul State, Brazil (see **Figure 1.3**) were used for this research, comprising approximately 560 km:

- i. BR-116: km 0 - km 234.7
- ii. BR-158: km 158.3 - km 322.6
- iii. BR-386: km 180.2 - km 346.1

The inventory data were collected in 2014 within the BR-Legal Program of the National Department of Transport Infrastructure (DNIT) and contained information about horizontal alignment, vertical alignment, and cross-section. The three roads connect the geological regions of the Northern Highland Plateau with the Central Depression. Consequently, they all have some extension of their alignment through mountainous terrain (dark green in **Figure 1.3**). **Table 1.1** summarizes the main characteristics of the three roads.



Figure 1.3: From left to right (in red): BR-158; BR-386 and BR-116 in Rio Grande do Sul state (Brazil)

Table 1.1: Roads' features summary

Variable	BR-116	BR-158	BR-386
Minimum curve radius	25 m	87 m	105 m
Maximum deflection angle	164°	102°	119°
Maximum ramp grade	11%	10%	6,8%
Lane width variation	6.60 - 7.50 m	6.20 - 7.20 m	6.70 - 7.50 m
Maximum AADT	15,000	9,450	9,050

1.4.2. CRASH DATA

In addition to the road inventory dataset, georeferenced crash data comprising three years (2017-2019) was used from the Road Federal Police (PRF) database. The datasets of 2017 to 2019, considering the interest segments, had initially about 2,500 registers of traffic crashes involving roughly 5,500 individuals. **Table 1.2** shows some of the variables in the police records and briefly describes them.

Table 1.2: Crash variables

Variable	Description
Hour	5 minutes approximation
Date	dd/mm/yyyy
Day period	night; day; dusk; dawn
Type of crash	collision with pedestrian; fixed object collision; head-on collision; lateral collision; rear-end collision; rollover; run-off-road; side collision; among others
Cause	speeding; alcohol-related; vehicle failure; inattention; visibility restrictions; unsafe following; sleeping; roadway conditions; among others
Weather	clear sky; cloudy; foggy; sunny; hail; light rain; rainy; snow; windy
Lane direction	ascending; decreasing (considers the point of collision)
Lane configuration	single; two-lanes; multiple lanes
Road configuration	curve; tangent; intersection; bridge; tunnel; among others
Number of victims	classified by fatal; severe injury; light injury; no injury
Number of vehicles involved	-
Vehicle type	bus; car; heavy truck; motorcycle; small truck; among others
Vehicle manufacturing year	-
Subject	driver; passenger; pedestrian
Sex	female; male
Age	-

The thesis focused on crashes where road geometry had potentially played a significant role; therefore, some types of crashes were filtered out, such as the ones that occurred in urban areas, intersections, temporary detours, and running over animals, among others. Furthermore, some of the crashes were excluded due to location imprecision. In the end, information about drivers' directions (northbound/southbound) was obtained from the individual analysis of each Bulletin of Traffic Accident (BAT) for the remaining crash occurrences.

1.4.3. TRAFFIC COUNTS

Traffic count data came from two sources: (i) the road inventory data collected in 2014 within the BR-Legal Program, which included traffic count surveys distributed in the researched road network, and (ii) the Traffic Count National Plan (PNCT) (DNIT, 2020), which was also used to update the 2014 data. According to them, there was no significant change in the Annual Average Daily Traffic (AADT) during the three years evaluated; therefore, a unique AADT value was adopted.

The road network was divided into twenty-two segments with homogeneous AADT, and the approximate traffic volume per hour (vph) connected to the crash location and time was calculated considering the estimated hourly pattern of each road segment and the day of crash occurrence (weekday or weekend/holiday). **Table 1.3** describes the road segmentation adopted.

Table 1.3: AADT segments

Segment	Road	Start (location)	End (location)	Length (km)	AADT
1	116	DIV SC/RS (FIM PONTE S/RIO PELOTAS)	ENTR BR-285(A) (P/VACARIA)	37.3	5 579
2	116	ENTR BR-285(B) (VACARIA)	ENTR RS-122 (P/IPÊ)	18.9	3 809
3	116	ENTR RS-122 (P/IPÊ)	ENTR RS-437 (CAMPESTRE DA SERRA)	22.1	1 899
4	116	ENTR RS-437 (CAMPESTRE DA SERRA)	ENTR AV VENÂNCIO AIRES (SÃO MARCOS)	35.5	2 811
5	116	ENTR AV VENÂNCIO AIRES (SÃO MARCOS)	ENTR RS-230 (ANA RECH)	27.0	2 949
6	116	ENTR AV. SÃO LEOPOLDO (CAXIAS DO SUL)	ENTR RS-452 (VILA CRISTINA)	18.2	1 629
7	116	ENTR RS-452 (VILA CRISTINA)	ENTR RS-235 (P/NOVA PETRÓPOLIS)	12.0	3 573
8	116	ENTR RS-235 (P/NOVA PETRÓPOLIS)	ENTR R. VICENTE PRIETO (PICADA CAFÉ)	10.8	7 581
9	116	ENTR R. VICENTE PRIETO (PICADA CAFÉ)	ENTR VRS-873 (P/SANTA MARIA DO HERVAL)	20.2	14 516
10	158	ENTR BR-285 (P/PANAMBI)	ENTR RS-553 (P/PEJUÇARA)	15.2	1 860
11	158	ENTR RS-553 (P/PEJUÇARA)	ENTR BR-377(A) (CRUZ ALTA)	20.8	1 847
12	158	ENTR BR-377(B)/RS-342 (CONTORN. CRUZ ALTA)	ENTR BR-481(A) (P/SALTO DO JACUI)	7.2	6 054
13	158	ENTR BR-481(A) (P/SALTO DO JACUI)	ENTR BR-392(A) (TUPANCIRETÃ)	34.9	3 750
14	158	ENTR BR-392(A) (TUPANCIRETÃ)	ENTR RS-527 (P/JÚLIO DE CASTILHOS)	23.2	5 354
15	158	ENTR RS-527 (P/JÚLIO DE CASTILHOS)	ENTR RS-348 (VAL DE SERRA)	29.3	5 142
16	158	ENTR RS-348 (VAL DE SERRA)	ENTR RS-509 (P/SANTA MARIA)	29.2	4 169
17	386	ENTR BR-285/377(B) (P/PASSO FUNDO)	ENTR BR-153(A)/RS-223 (P/TAPERA)	34.6	3 943
18	386	ENTR BR-153(B)/RS-332(A)	ENTR RS-332(B) (P/ARVOREZINHA)	2.6	8 559
19	386	ENTR RS-332(B) (P/ARVOREZINHA)	ACESSO P/FONTOURA XAVIER	19.3	9 223
20	386	ACESSO P/FONTOURA XAVIER	ENTR RS-423 (P/PROGRESSO)	44.9	8 311
21	386	ENTR RS-423 (P/PROGRESSO)	ENTR R. BRASIL (MARQUÊS DE SOUZA)	10.0	8 216
22	386	ENTR R. BRASIL (MARQUÊS DE SOUZA)	ENTR RS-421 (P/FORQUETINHA)	16.7	10 213

1.5. THESIS STRUCTURE

This document is structured into eight chapters. The current chapter, Introduction, outlines the road safety perspective adopted throughout the thesis. Moreover, relevant information and context are given to understand the general development of the research. The six papers composing this document are presented in the subsequent chapters (2 to 7), detailed in the following paragraphs. The final chapter, **Chapter 8**, presents a critical analysis highlighting the main research results, limitations, conclusions, and guidelines for further research on the theme.

Chapter 2 presents the first paper, *Driving Simulator for Evaluating the Effects of Road Geometric Design on Driver Behavior: Protocol of a Systematic Review*, published in the International Journal of Occupational and Environmental Safety. A published protocol is a component of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines adopted in the systematic review. Therefore, Chapter 2 can be seen as a prologue to the next chapter, stating relevant information and procedures adopted in the systematic review of Chapter 3.

Chapter 3 is dedicated to paper number two and contains the systematic review itself. The second paper, *Driving Simulators to Evaluate Road Geometric Design Effects on Driver Behaviour: A Systematic Review*, was published in the Accident Analysis and Prevention journal. It is a methodic, thoroughly developed review of 34 studies that aimed to identify gaps in the literature and the best practices for driving simulator experiments.

Chapter 4 is directly related to the driving experiment performed within this thesis scope. The third paper, *A Novel Approach to set Driving Simulator Experiments based on Traffic Crash Data*, published in the Accident Analysis and Prevention journal, is the first step to defining the scenarios used in the simulator. It responds to a lack of methodology to base studies' choices on developing simulated scenarios considering crash data.

Chapter 5 is related to the paper *New Version of Driver Behaviour Questionnaire to investigate Driver Behaviour on Rural Roads*, presented and published in the Annals of the 35° Congress of Research and Education in Transport of ANPET. The new version was intended to adapt the DBQ to the thesis context, including modern habits and rural road driving situations. This paper tackles another critical point in the research: measuring driver profile.

Chapter 6 presents the fifth paper *Evaluating Individual Heterogeneity in the Probability of Crash Involvement*, presented at the 2022 Road Safety and Simulation International Conference, where the extended abstract was published. This paper analyzes the relationship between the Driver Behavior Questionnaire and crash occurrence. It discusses the systematic human share related to crashes measured by the DBQ.

Chapter 7, the sixth and final paper, *The Influence of Driver Profile on Driving Performance: A Simulator Study*, presented at the 2022 Road Safety on Five Continents, published in the Accident Analysis and Prevention journal, presents the results of the driving simulator experiment with 56 participants performed within the scope of this thesis. This paper builds on the other papers' insights, wrapping up the knowledge of road-driver interaction provided by the thesis' efforts.

2

DRIVING SIMULATOR FOR EVALUATING THE EFFECTS OF ROAD GEOMETRIC DESIGN ON DRIVER BEHAVIOR: PROTOCOL OF A SYSTEMATIC REVIEW

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This chapter presents the first paper, a protocol of the systematic review, an indivisible part of the next chapter's paper. The PRISMA guidelines followed in the systematic review recommend a published protocol.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) provides a detailed guideline on the conducting process and a set of items for improving quality in systematic reviews and meta-analyses. The method advocates for the publication of the systematic review protocol, a document containing complete information about the processes, explicitly documenting what was planned. This document enables other researchers to compare, replicate, and judge the review methods, reducing bias and increasing transparency of systematic reviews (Shamseer et al., 2015).

The protocol was published in June 2019, and the systematic review was published in February 2021. No major deviations from the plan occurred. In essence, the protocol was important to planning, registering, and disseminating the rationale and details of the performed systematic review.

ABSTRACT

The traditional approach adopted towards road safety is the analysis of risk factors that contribute to the frequency or severity of traffic crashes. Many distinct elements play a role, simultaneously, in a crash occurrence, and, undoubtedly, the geometric design of highways and its effect on human behavior are part of that equation. A valuable tool to investigate this interaction is the driving simulator. Nevertheless, experiment design, participants' features, and data acquisition are detrimental factors for the effective use of this tool. This systematic review protocol is based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Protocols (PRISMA-P) Statement and presents a method to find evidence on driving simulator studies of road geometry effects on drivers' behavior.

KEYWORDS: Driving Simulator, Road Geometry, Road Safety

2.1. INTRODUCTION

2.1.1. RATIONALE

A traditional approach to road safety is to identify risk factors that contribute to the frequency or severity of crashes (De Oña, López, Mujalli, & Calvo, 2013; Dingus et al., 2016; Gibson, Heaton, & Tass, 2018; Papadimitriou et al., 2019; Papadimitriou & Theofilatos, 2017; Zhang, Yau, & Chen, 2013). Many distinct agents play a role in crash occurrence and crash outcome, simultaneously. Commonly, they are divided into three main aspects: human, road environment, and vehicle-related causes.

Among the road environment causes, road geometric design deficiencies represent a risk for crash occurrence. In the analysis made within the Safety Cube Project, there were identified 59 specific risk factors related to the road environment that potentially played a role in accidents frequency and severity (Papadimitriou et al., 2019). Between them, a low curve radius was considered the riskiest deficiency related to road alignment. Aspects of road design are also taken into account in the Infrastructure Risk Rating Manual for Australian Roads (Zia, Harris, Smith, & Anderson, 2019), specifically, lane and shoulder width and horizontal alignment (degrees of turn per km) increase road risk rate.

Understanding driver-roadway interaction can enhance road design strategies to create a safer environment for their users. With this purpose, a powerful tool to assess those two components is a driving simulator. This technique has the advantage of testing and comparing different existing or even new road configurations and how drivers perceive and react to them. It allows to manipulate confounding variables, reproduce repetitively identical situations for each participant, simulate hazards that rarely occur or risky situations, without engaging drivers in dangerous activities. Furthermore, since their early application in the 1960s, they have proved to be capable of addressing a wide range of research questions (Fisher, Rizzo, Caird, & Lee, 2011).

Nevertheless, despite driving is an ordinary daily task for many people, it is also the most complex one, involving perceptual, psychomotor and cognitive skills (Fisher et al., 2011). Experiment design, participants' enrolment, sample size, undertaking of the driving activity, and data acquisition are detrimental factors for the effective use of this tool. Problems of inconsistency and inaccuracy can prevent that scientific literature meet all the needs of road safety research for evidence-based findings. In a research regarding driving simulator experiments on the effects of driver distraction, it was reported that the experiments vary considerably in terms of sample characteristics, design, and analysis methods, exposing a lack of uniformity in the way they are conceived, conducted, and exploited (Papantoniou, Papadimitriou, & Yannis, 2015).

Furthermore, Wynne, Beanland, & Salmon (2019) when analyzing driving simulator validity studies in a systematic review found no straightforward relationship between simulator fidelity and validity, which can raise the doubt if other elements, such as experiment procedure, could be influencing studies' outcomes. They also highlighted the lack of detailing when studies reported the simulated driving environment and the outcomes of statistical analyses.

Therefore, a systematic search of the literature will be undertaken to outline how studies are implementing this interdisciplinary research method regarding road geometry and driver behavior and what the pieces of evidence related to road design effects and driver behavior in simulated environments.

2.1.2. OBJECTIVES

The objective of this research is the critical review of driving simulator studies on driver behavior affected by road geometry. A comparative and quality evaluation of the design and implementation of driving simulator experiments will be carried out for primary components – covering drivers' characteristics and sample variability, experimental procedure protocols, studied road features and drivers' behavior data. Furthermore, if the included studies are sufficiently homogenous, a quantitative

synthesis will be performed to examine evidence regarding the relationship between a specific road geometry feature (radius of horizontal curves, lane width, shoulder width, among others) and driver performance measures (average speed, lane position variability, among others).

2.2. METHODS

2.2.1. ELIGIBILITY CRITERIA

Studies that used a driving simulator to test driver's behavior that considered the influence of the road geometry characteristics will be contemplated.

Only studies available online and published in English will be included. Articles and Conference Papers will be admitted, allowing this review to access the most recent and relevant papers in this field.

Since driving simulation technology that is being used nowadays and the current process of carrying on this type of experience are also relevant factors in this review, studies from 2014 to 2019 will be included in the initial search strategy, once the aim is to access how the recent studies have been performing these experiments. Nevertheless, it will be considered a backward snowballing approach (Wohlin, 2014) when identified relevant studies for the objective of this review, so the period can be extended in this case.

Papers that do not influence a geometric road element and its effects on human behavior as a main topic of the study will be excluded. Since road geometry is a broad subject, in this review studies that only focused on specific situations such as intersections/junctions/roundabouts, u-turns, acceleration lanes, and auxiliary lanes will be excluded. Studies that only considered an urban environment will also be excluded, because traffic volume, presence of pedestrians, road environment (buildings/houses), road signage, and density of intersections are too diverse from the studies that considered a rural environment, where, due to fewer variables, road geometry tend to have a more significant effect on driver's behavior.

In addition, specific physical health conditions will be excluded such as drug usage, diseases, or physical and cognitive conditions. However, fatigue a priori, will not be excluded, since it is a state that can be caused by driving activity itself.

2.2.2. INFORMATION SOURCES

The main multidisciplinary and engineer-focused databases will be contemplated during the planned period of January 2019. Databases will be: ASCE Library, INSPEC, Safety Lit, Sage Journals, Science Direct, Scopus, Springer, Taylor & Francis, TRID - Transportation Research Board, Web of Science, and Wiley Online Library.

2.2.3. SEARCH STRATEGY

The search strategy will include the study population using terms and keywords derived from the expertise of the reviewers in the subject field. Study population terms will include always "drive" or "driving" and "simulator" or "simulation". Most of the articles will be filtered by the reviewers not by the keywords since the aim is not to exclude papers that had studied geometric road features, but also considered other variables as well (for example, studies that included scenarios with and without guardrail barriers). Since road geometry is a broad subject, in the search strategy, studies that contained subjects such as autonomous driving, in-vehicle or onboard devices, and medical perspectives of drug usage, diseases, and physical and cognitive conditions will be excluded. Search strategies for all databases with detailed search terms, linkage with logical operators, and combined queries are described in the **Supplementary Material**.

To complete the catalog of studies, a snowballing process (Wohlin, 2014) will be undertaken to find relevant articles examining studies references exclusively related to the identified topic (geometric

parameter) for a potential meta-analysis. Moreover, the studies catalog will be updated until the conclusion of the systematic review considering the three identified databases with more studies elected.

2.2.4. STUDY RECORDS

Records will be managed through Mendeley, a specific software for managing bibliographies.

All the results from the search strategy will be reviewed and selected based on their title and abstract and duplicates will be removed. After that, studies will have their full text analyzed and will be selected for the data synthesis stage. This process will be guided by the eligibility criteria. The selection process will be carried out by two reviewers (MB/MS) independently, and a third reviewer (SF) will resolve in case of disagreement.

The process of data extraction will be performed by two reviewers (MB/MS) searching for information sources independently. Each of the two review authors (MB/MS) will extract data on half of the studies, and check for accuracy on the other half. A third reviewer (SF) will independently check the data for consistency and clarity.

The initial records identified for the first and second reviewers will be shared to confirm coding decisions for the worksheet created based on the review objectives. Once there is an agreement on the coding and variables to be searched from the initial studies, the rest of the studies will be coded without sharing between reviewers unless it is identified a new situation, so the process will be restarted for that specific issue.

If the included studies are sufficiently homogenous regarding variables analyzed and outcomes measures and also were at least classified as “moderate” or “good” by the quality assessment tool, a quantitative analysis will be performed independently by one reviewer (MB) and a second reviewer (MS) will check for accuracy.

2.2.5. DATA ITEMS

Beyond data related to the identification of the study (title, authors, year), data extracted will include information from the following summary: leading institution and country, description of the driving simulator, type of the road scenario (number of lanes, directions), number of scenarios, route length, number of drives per participant, ordering of scenarios/studied elements, presence or absence of a practice trial before the principal test, trial duration, break duration, final number of participants in the sample and their characteristics (sex; age mean, range, and standard deviation; social background), sampling method, requirements and justification for the sample, if participants were excluded and the motives and methods of exclusion, objective of the study, measures of outcomes, analyzed road geometry feature, main methods and results, limitations/biases stated and remarks for interesting information that the study might provide.

2.2.6. OUTCOMES AND PRIORITIZATION

For the purpose of this review, the initial focus will be how driving simulator experiments about road geometry effects on driver behavior are being performed and their main findings. Characteristics of the equipment, protocols for experiments, participant's enrollment process and their features, how the exclusion of participants was undertaken, etc. Furthermore, studies will be mainly classified based on the experiment procedures' quality, however, aspects of the simulation equipment and statistical treatment of data will be considered as well (see 2.2.7).

Secondly, for each road geometry feature a summary of the main findings will be conveyed. Finally, the most frequently evaluated road geometry and parameter of driving behavior will be identified and if possible, a comparison of outcomes from different studies will be performed.

2.2.7. RISK OF BIAS IN INDIVIDUAL STUDIES

The quality of the studies will be independently assessed by one reviewer (MB) and a second reviewer (MS) will check for accuracy.

Quality assessment was based on NIH quality assessment tools (National Heart Lung and Blood Institute, 2019) for different types of studies. However, considering the expertise of the research group, a particularized tool (see *Erro! Fonte de referência não encontrada.*) to assess the quality of the experiments will be applied.

Table 2.1: Quality assessment questions and possible answers

Simulation	1.1	Was driving simulator apparatus suitable for the research intent?	(Y/N/NR)
	1.2	Was a method of randomization or counterbalance of scenarios performed?	(Y/N/NR/NA)
	1.3	Was a method of randomization or counterbalance of geometries performed?	(Y/N/NR/NA)
Sample	2.1	Does the sample represent target population?	(Y/N)
Procedure	3.1	Was a practical trial performed?	(Y/NR)
	3.2	Was a method to assess driver's familiarization with the simulator specified?	(Y/N/NR/NA)
	3.3	Was motion sickness assessed?	(Y/NR)
	3.4	Was there a clear description of the method to assess motion sickness?	(Y/N/NR/NA)
	3.5	Was the existence of outliers assessed?	(Y/NR)
	3.6	Was there a clear description of the method to assess outliers?	(Y/N/NR/NA)
Data analysis	4.1	Was a statistical method of analysis applied?	(Y/N)

The driving simulator apparatus will be considered suitable for the research intent if the interest variables in the study match with the minimum simulator requirements considering the Degrees of Freedom (DOF) of the simulator motion system and the horizontal projected Field of View (hpFOV) (see *Erro! Fonte de referência não encontrada..2*). Complex geometry is considered the analysis of the influence of transition curves in horizontal curves, vertical alignment (grade), and superelevation, among others. No consideration regarding the suitability of simulators for comparison of different scenarios will be made. Furthermore, since results will be presented exclusively regarding drivers' performance (see **2.2.8**) the high-level simulator requirement will be applied only if the study did not analyze performance aspects as well.

Table 2.2: Study's analyzed variables and simulator minimum characteristics

Study evaluation	Minimum hpFOV	Minimum DOF
Physiological and Subjective (only)	180°	6
Performance and basic geometry	40°	0
Performance and complex geometry	120°	6

If more than one scenario is presented to drivers, and order effects could influence the result of the study, studies will be classified regarding the order of scenarios. If the order of geometry parameters in a scenario could affect results, they will also be classified accordingly.

The next stage contemplates the participants' sample. Studies will be positively classified in this category if they state a target population and provide sample characteristics clear enough to be possible to confirm this.

The final stage assesses typical experimental procedures of a driving simulator: if a practical trial was performed, if studies used a method to assure the driver's familiarization with the simulator if motion

sickness and presence of outliers were examined, and the methods to do so. For sickness assessment, studies that reported cases of participant dropout will be positively classified in question 3.3, but negatively classified in question 3.4. If studies did not provide information about the existence of practical trials, motion sickness, and outliers assessment (questions 3.1, 3.1, and 3.4) they will be marked as neutral (Not applicable) in questions 3.2, 3.4, and 3.6.

Possible answers to the questions are: Yes (Y), No (N), Not reported (NR), and Not applicable (NA). Studies will be classified as weak, moderate, or strong based on their scores below(1).

$$Score = \frac{\sum Y}{total\ number\ of\ questions - \sum NA} \quad (1)$$

Table 2.3: Classification of studies based on their scores

Classification	Score
weak	0 ---0.4
moderate	0.4 ---0.7
strong	0.7 ---1

2.2.8. DATA SYNTHESIS

Data synthesis will be presented as a narrative assessment of the evidence of the effects of road geometry on drivers' behavior divided by the type of geometric feature analyzed. If there is not a clear division of each geometric feature influence, results will be combined in a more general division, such as horizontal alignment or vertical alignment.

Outcomes will be reported only regarding driving performance (actions). Hence, outcomes from studies that focused only on physiological or subjective measures will not be synthesized, since the interest is to assess how road geometry conditions drivers' actions. High-rated studies, based on the quality assessment tool, will be presented first.

In the possible identification of sufficient homogeneous studies evaluating the same specific road geometry (for example, curve radius, lane width, shoulder width, grade, among others) and outcome (for instance, average speed or average lateral position, among others), a meta-analysis will be performed. We anticipate that the heterogeneity of outcome measures will allow only an exploratory analysis with a possible comparison between studies' results.

2.3. REGISTRATION

Important protocol amendments post-registration will be recorded and included in dissemination.

SUPPLEMENTARY MATERIAL

Databases	Strings
ASCE Library and Science Direct	("driving simulator" OR "driving simulation") AND (road OR roadway OR highway) NOT (automated OR alcohol OR patient OR "in-vehicle")
INSPEC	("driving simulator" or "driving simulation" or "drive simulator" or "drive simulation") and (road* OR highway) and (infrastructure or alignment or characteristic or feature or design or geometry or environment or "design consistency" or shoulder or "lane width" or "vertical alignment" or "horizontal alignment" or grade or superelevation or slope or ramp or curve) not (automatic or autonomous or automated or "in-vehicle" or "on board" or patient or alcohol)
Safety Lit	((("driving simulator" OR "drive simulation" OR "driving simulation" OR "drive simulator" AND roadway OR highway) NOT drug OR alcohol OR patient) NOT autonomous OR automated OR automatic OR "in vehicle" OR "on board")
Sage Journals, Taylor & Francis and Wiley Online Library	("driving simulator" OR "driving simulation" OR "drive simulator" OR "drive simulation") AND (road* OR highway) AND (infrastructure OR alignment OR characteristic OR feature OR design OR geometry OR environment OR "design consistency" OR shoulder OR "lane width" OR "vertical alignment" OR "horizontal alignment" OR grade OR superelevation OR slope OR ramp OR curve) NOT (automatic OR autonomous OR automated OR "in-vehicle" OR "on board" OR patient OR alcohol)
Scopus	TITLE-ABS-KEY ("driv* simulat*" AND road* OR highway AND "road* infrastructure" OR "road* alignment" OR "road* characteristic" OR "road* feature" OR "road* design" OR "road* geometry" OR "road* environment" OR "design consistency" OR shoulder OR "lane width" OR "vertical alignment" OR "horizontal alignment" OR grade OR superelevation OR slope OR ramp OR curve AND NOT automat* OR autonomous OR "in-vehicle" OR "on board" OR patient OR alcohol)
Springer and Web of Science	"driv* simulat*" AND (road* OR highway) AND ("road* infrastructure" OR "road* alignment" OR "road* characteristic" OR "road* feature" OR "road* design" OR "road* geometry" OR "road* environment" OR "design consistency" OR shoulder OR "lane width" OR "vertical alignment" OR "horizontal alignment" OR grade OR superelevation OR slope OR ramp OR curve) NOT (automat* OR autonomous OR "in-vehicle" OR "on board" OR patient OR alcohol)
TRID Transportation Research Board	"driv* simulat*" and (road* or highway) and ("road* infrastructure" or "road* alignment" or "road* characteristic" or "road* feature" or "road* design" or "road* geometry" or "road* environment" or "design consistency" or shoulder or "lane width" or "vertical alignment" or "horizontal alignment" or grade or superelevation or slope or ramp or curve) not (automatic or autonomous or automated or "in-vehicle" or "on board" or patient or alcohol)

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3

DRIVING SIMULATORS TO EVALUATE ROAD GEOMETRIC DESIGN EFFECTS ON DRIVER BEHAVIOUR: A SYSTEMATIC REVIEW

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Accident Analysis & Prevention

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This chapter presents the second paper of the thesis: the systematic review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), a recognizable method intended to guarantee complete and improved reporting. Recently, the PRISMA guidelines were updated to reflect advances in systematic review methodology and terminology (Page et al., 2021).

The systematic review focused on road design's effects on driver behavior, an elementary subject of the thesis. The paper synthesizes the state of practice and knowledge, critically appraising thirty-four studies included in the final analysis and identifying research priorities.

The restriction regarding the driving simulator was to limit the review's scope and gain knowledge of the state of the practice using this research tool. Therefore, it was possible to identify best practices and problems and make suggestions to amend these issues in future driving simulator experiments, including this thesis's driving simulator experiment.

This paper represents a cornerstone of the thesis, and its insights influenced all the work that followed.

ABSTRACT

Several factors can influence driver behaviour, and road geometry is one of them. A better understanding of driver-roadway interaction can enhance road design to create a safer traffic system. In this context, driving simulators are powerful tools that combine convenience and effectiveness in identifying drivers' responses to different geometry factors. In this paper, a systematic review following a Prisma guideline was conducted on driving simulator studies that examined the effects of road geometry on driver behaviour to reveal the current procedures adopted in this field and their main findings. A systematic search of eleven databases was performed covering six years of research results. The inclusion of relevant studies focused on horizontal curves, a topic identified as the most cited, extended this period. The results revealed significant heterogeneity in relation to the measured variables and deficiencies when reporting the experiment, which prevented a meta-analysis of the studies' outcomes. Despite this, a discussion of the potential of driving simulators to contribute to several road safety research gaps is presented. In addition, problems of a lack of standardisation in the performance of the experiments were detected, potentially influencing the findings of the studies. However, the results also suggest that experiments that followed good experimental practices observed effects on driver performances not detected by other studies.

KEYWORDS: Driving Simulator; Road Geometry; Road Safety; Driver Behaviour

3.1. INTRODUCTION

A traditional approach to road safety is to identify risk factors that contribute to the frequency or severity of crashes (Dingus et al. 2016; Gibson et al. 2018; de Oña et al. 2013; Papadimitriou et al. 2019; Papadimitriou and Theofilatos 2017; Zhang et al. 2013). Since many distinct agents simultaneously play a role in a crash occurrence and outcome, they are commonly divided into three main aspects: human, road environment, and vehicle.

Among the road environment factors, road design deficiencies are a risk for crash occurrences (Elvik et al. 2009; Papadimitriou et al. 2019; Zia et al. 2019). Furthermore, a low curve radius was considered the riskiest deficiency related to the road alignment (Papadimitriou et al. 2019), but also lane width, shoulder width, and horizontal alignment (degrees of turn per km) were related to an increase in road risk rate (Zia et al. 2019).

Understanding driver-roadway interaction can enhance road design strategies to create a safer environment since road design guidelines typically do not consider driver behaviour and are often based on the physics of vehicles and pre-determined design speed. Therefore, driving simulators emerge as a powerful tool to analyse these interactions. Driving in a simulated environment has the advantage of testing and comparing different existing or even new road configurations, determining how drivers perceive and react to them. It allows studies to manipulate confounding variables, reproduce repetitively identical situations for each participant, and simulate hazards that rarely occur or risky situations without engaging drivers in dangerous activities. Arguably, the simulated environment can never perfectly reproduce real-world conditions in terms of scenario or drivers' motivation, affecting drivers' responses; however, since their early application in the 1960s, they have successfully addressed a wide range of research questions (Allen et al. 2011).

Furthermore, there is a continued interest in studying road infrastructure because it is a persistent safety issue worldwide, which is why ensuring a safer road environment remains a pillar to guiding global actions in preventing accidents (WHO 2018). Therefore, considerable research has been done to explore the relationship between road characteristics and driver behaviour. However, not only should efforts be made concerning where further understanding is needed, but also findings of studies must be analysed critically to ensure robust evidence-based information.

In the context of driving simulator studies, experiment design, participants' enrollment, sample size, driving activity, and data acquisition are detrimental factors for the effective use of this tool. Problems of inconsistency and inaccuracy when conducting and reporting these experiments can prevent studies from producing reliable results. As an example, in a study regarding driving simulator experiments on the effects of driver distraction, the authors reported that the experiments varied considerably in terms of sample characteristics, design, and analysis methods, exposing a lack of uniformity in the way they are conceived, conducted and exploited (Papantoniou et al. 2015).

Furthermore, when analysing driving simulator validity studies, Wynne et al. (2019) found no straightforward relationship between the fidelity and validity of the simulators, which may raise doubts about whether other elements, such as experiment procedures, may be influencing studies' outcomes. The authors also highlighted the lack of detailing when reporting the simulated environment, as well as the statistical analysis results.

Therefore, a systematic search of the literature was performed to outline how studies have been implementing this interdisciplinary method regarding road geometry and driver behaviour, and what is the knowledge revealed by the studies. A comparative and qualitative evaluation of the design and implementation of driving simulator experiments was carried out, and a quantitative synthesis was planned to examine evidence regarding the relationship between road geometry features and drivers' objective measures. However, due to the lack of sufficient homogeneous studies evaluating the same

geometry and outcome, the initially planned meta-analysis could not be performed. Nevertheless, data synthesis is presented as a summary narrative about the evidence of the road geometry effects on driver behaviour, by type of feature analysed. Moreover, a critical analysis of these results concerning the knowledge gaps found in the literature on accident risks is presented. Outcomes are reported only regarding driving performance (speed, acceleration, lateral position, among others).

3.2. METHODS

3.2.1. PRISMA STATEMENT AND PROTOCOL

The review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The PRISMA statement provides a detailed guideline on the conducting process, as well as a set of items for improving quality in systematic reviews and meta-analysis. Initially intended to address the issue of suboptimal reporting in the health care field, it was later updated to cover several conceptual and practical advances in the science of systematic reviews, including other types of research (Moher et al. 2009). Moreover, the PRISMA method is particularly interesting to compare studies based on experiments because the way that experiments are conducted may affect their results, an analysis that in a typical review would not be so stressed.

The method also advocates for the publication of the systematic review protocol, a document containing complete information about the processes, explicitly documenting what was planned. This document enables other research to compare, replicate, and judge the review methods, also preventing selective reporting (Shamseer et al. 2015). The protocol for this review was published in the International Journal of Occupational and Environmental Safety (Bobermin et al. 2019).

3.2.2. ELIGIBILITY CRITERIA

Firstly, this review searched for studies that used a driving simulator and had as the main topic the effects of road geometry on drivers' behaviour. Therefore, studies focusing on rural settings were pursued. On rural roads, road geometry tends to have more influence due to the lower participation of other variables (for example, traffic volume, pedestrians, and bicycles, crossing lanes, buildings, houses, and frequency of road signs and intersections). Consequently, vehicles are typically under free-flow conditions, and drivers' choice of speed and trajectory reflects better drivers' response to road geometric characteristics than in an urban environment (Török 2011). The initial search strategy selected studies from 2014 to 2019 (both included). Nevertheless, due to a snowball approach (Wohlin 2014), the period was extended until 1996 for studies that had horizontal curve radius as the main topic, since it was identified as the leading subject in the initial search period.

Studies that considered specific physical health conditions, such as drug usage, diseases, or physical and cognitive conditions, were excluded. Fatigue is another frequent topic in this field, but it was not excluded without a further look since this is a state that may be caused or influenced by the road geometry (Farahmand and Boroujerdian 2018).

The main multidisciplinary and engineer-focused databases were considered: ASCE Library, INSPEC, Safety Lit, Sage Journals, Science Direct, Scopus, Springer, Taylor & Francis, TRID - Transportation Research Board, Web of Science, and Wiley Online Library.

3.2.3. SEARCH STRATEGY

The first search used terms and keywords derived from the group's expertise in the subject field. Mandatory study population terms included "drive" or "driving" and "simulator" or "simulation". All the studies identified by the search strategy were then filtered and selected based on their title and abstract. After this, the full texts of the studies were analysed to be included in the data synthesis stage.

The eligibility criteria guided this process, and two reviewers (MPB/MMS) carried out the selection process independently. The third reviewer (SF) mediated disagreements.

3.2.4. DATA COLLECTION PROCESS AND DATA ITEMS

Each of the two reviewers (MPB/MMS) extracted data from half of the selected studies and verified the data extracted by the other reviewer from the other half. Reviewers shared initial records catalogued on a worksheet to confirm coding decisions; once an agreement was reached, they continued the process independently. In the end, the third reviewer (SF) verified the consistency and clarity of the data.

3.2.5. RISK OF BIAS IN INDIVIDUAL STUDIES

The experiments' assessment was based on NIH quality assessment tools (National Heart Lung and Blood Institute 2019) for different types of studies. However, considering the research group's experience, a special tool developed for driving simulator experiments was used. It is essential to highlight that the tool focused mainly on technical experiment practices and does not evaluate the overall quality or significance of the research. Furthermore, a low score in the assessment tool does not mean that the study's findings are misleading, but there was not a clearly stated control for some factors. More details about the assessment tool can be found in the protocol of this review in the International Journal of Occupational and Environmental Safety (Bobermin et al. 2019).

3.2.6. DATA SYNTHESIS

Data synthesis is presented as a summary narrative about the evidence of the road geometry effects on driver behaviour, by type of geometric feature analysed. The summary is divided into five sections, comprising the influence of horizontal curve, transition curves, shoulder width, lane width, and vertical alignment. Although it is recognised that other authors, not focusing only on driving simulator experiments, pointed out the influence of variables such as superelevation, tangent length, vertical grade, and the radius of the previous curve (Castro et al. 2012), those five elements represented the most cited geometry among the studies retrieved, considering the period of publications searched.

Similarly, as can be seen in **Table 3.1**, the studies measured different variables, but measures related to the performance of the drivers are the most investigated. Therefore, the outcomes of the five main topics are reported regarding driving performance (speed, acceleration, lateral position, among others). Furthermore, an appraisal between the studies' findings and research gaps from the literature on accident risks are conveyed for each geometry.

3.3. RESULTS

3.3.1. STUDY SELECTION

The process of identification, screening, and inclusion of eligible studies is summarised in the flow diagram in **Figure 3.1**. The combined search of the two reviewers identified 5,911 studies. From those, 3,630 articles did not meet the eligibility criteria of date, document type, and language. For the remaining 2,281 reports, the titles and abstracts were analysed, and 2,062 articles did not meet the requirements about the use of a driving simulator for testing driver behaviour and the influence of the road geometry characteristics. Hence, 219 articles were selected based on their title and abstract.

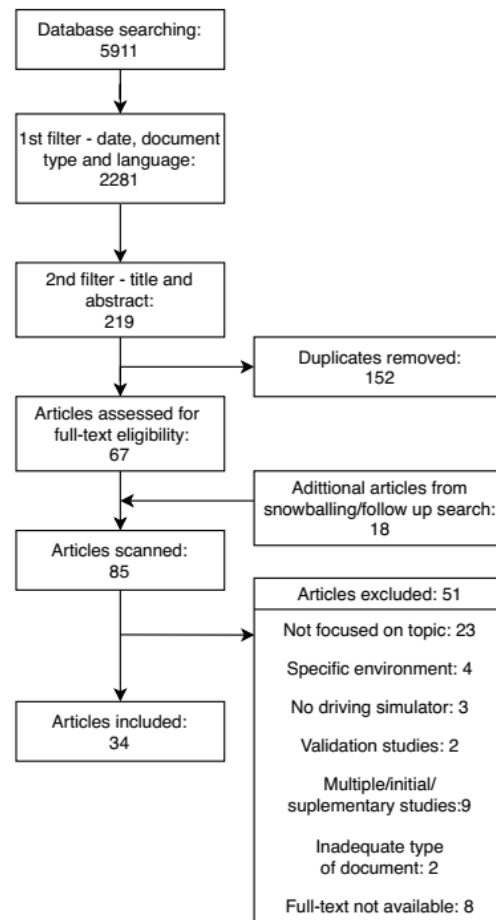


Figure 3.1: The identification, screening and inclusion process of eligible studies adopted

Some included articles appeared in more than one database; therefore, duplicates were removed, and 67 articles remained to review the full texts. Bibliographical references of relevant articles were analysed in a search for potential studies inclusion, and a final follow up search was made. These processes added 18 reports. As eight potential articles were not available, in the end, the full texts of 77 articles were reviewed.

Afterwards, 43 articles were excluded for the following reasons: 23 articles did not have effects of road geometry on drivers' behaviour as a subject (elements of road geometry were present but in a diverse point of view), four articles had specific situations analysed (urban environment and off-ramp curve), three articles did not use a driving simulator, two articles were validation studies, nine articles were multiple/initial/supplementary studies of other articles already screened, and two were identified as an inadequate type of document (poster). Finally, for the data synthesis, 34 studies met the inclusion criteria.

3.3.2. CHARACTERISTICS OF STUDIES

The 34 studies selected for the review (see **Table 3.1**) cover a range of six years (2014-2019), despite the fact that a few were published before this since the snowball approach extended this period only for studies that had a horizontal curve radius as the main topic. Chinese and Italian research institutions are dominant in the number of papers that focused on the road geometry aspect and driver behaviour in a simulated environment. It is also from these countries that most motion-based driving simulators were used in this topic, although many studies from Italy and China also made use of a fix-based simulator (see **Table 3.2**).

Table 3.1: Summary of the selected studies

ID	Author, year	Institution, country	Measures	Type of measure	Analysed elements	Main method
1	Liu & Xu (2019)	Chang'an University, China	Operating speed and Perceived Speed	Performance and Subjective measures	Horizontal radius (5 levels)	Descriptive and Pearson Correlation Analysis
2	Bassani et al. (2019a)	Politecnico di Torino, Italy	Mean speed and standard deviation, and mean and standard deviation of the standardised dispersion of trajectory	Performance	Horizontal radius (four levels), curve direction, and distance of the sight obstruction (three levels)	ANOVA
3	Bassani et al. (2019b)	Politecnico di Torino, Italy	Speed reduction and lane position	Performance	Horizontal radius (four levels), curve direction, distance of the sight obstruction (three levels), age (three groups), and behavioural profile (three groups)	ANOVA
4	Barendswaard et al. (2019)	Tu Delft, The Netherlands	Lateral position and Time to Lane Crossing	Performance	Speed (two levels) and horizontal radius (two levels)	Two-way repeated ANOVA
5	Xie et al. (2019)	Wuhan University of Technology, China	Subjective workload, speed, and lane deviation	Performance and Subjective measures	Horizontal radius, slope grade, traffic flow, and sign information. Four levels of each item	Multivariate ANOVA
6	Jeong and Liu (2019)	University of Michigan, USA	The standard deviation of lateral position, the standard deviation of steering wheel angle, eye movements, and subjective workload Mean value of the lateral position, standard deviation of the lateral position, the maximum absolute value of the lateral position, maximum absolute value of the lateral position, the difference between maximum and minimum values of the lateral position, maximum and minimum value of the lateral acceleration Trajectory dispersion (considering the lateral position profiles, the average lateral position, and the segment length) and lateral position Average speed and lane position error, mean acceleration, average horizontal eye gaze, useful field of view (visual area), and the driving workload (EEG signals from four lobes)	Performance, Physiological, and Subjective measures	Road curvature (four levels of radius, same deflection angle), curve direction and stimulus-response-task	Linear-mixed effects analysis, ANOVA, Tukey's test
7	Mauriello et al. (2018)	University of Naples Federico II, Italy	Horizontal curve radius (8 levels, same deflection angle) and curve direction	Performance	Horizontal curve radius (8 levels, same deflection angle) and curve direction	CATANOVA and Bhapkar's test
8	Montella et al. (2018)	University of Naples Federico II, Italy	Horizontal curves radius (4 levels of radius and 3 levels of deflection angle) and direction, with and without clothoids	Performance	Horizontal curves radius (4 levels of radius and 3 levels of deflection angle) and direction, with and without clothoids	Student's t-test
9	Kang et al. (2018)	Korean Expressway Corporation Research Institute, Korea	Horizontal curve radius, centric angle, bend length and curve length (varied)	Performance and Physiological measures	Horizontal curve radius, centric angle, bend length and curve length (varied)	Student's t-test
10	Choudhari and Maji (2018)	Indian Institute of Technology Bombay, India	Critical average lateral acceleration	Performance	Design speed, horizontal curve radius, gradient, preceding tangent length, age and driving experience (all grouped into three categories)	Hierarchical Clustering

Table 3.1: Summary of the selected studies (continued)

ID	Author, year	Institution, country	Measures	Type of measure	Analysed elements	Main method
11	Farahmand and Boroujerdian (2018)	Tarbiat Modares University, Iran	Steering wheel movements, the standard deviation of steering wheel movements, and lane positioning ability (the area between trajectory and centerline)	Performance	Road geometry variety by cumulative delta angle (sharpness) of curves of the entire alignment (three levels)	Repeated ANOVA
12	Chen et al. (2018)	Tongji University, China	Lane departure	Performance	143 independent variables (among them: curvature, grade, speed, visibility, curve direction, type of horizontal alignment, lane travelling, slope type, and characteristics for the adjacent segment with different lengths). Considered six levels of adjacent segment length	Mixed multinomial logistic models
13	Zheng et al. (2018)	Kunming University of Science and Technology, China	Average speed, the standard deviation of the speed, reaction time	Performance	Vertical alignment (three levels), straight or horizontal curve (with two levels), and enclosure degree (by trees, four levels)	Regression analysis, Student's t-test and F-tests
14	Wang and Wang (2018)	Tongji University, China	Speed change behaviour (maximum and minimum speed on the curve)	Performance	Combined curves: downslope, upslope, crest, sag (considering the combined curves' radii, length of circular and transition curves, the curvature of adjacent segments, curvature changes between combined curves and adjacent segments, and grade and grade changes of each combined curve and their adjacent segments)	Multinomial logistic models
15	Sadia et al. (2018)	Technio Israel Institute of Technology, Israel	Average speed	Performance	22 geometry segments (vertical curve, horizontal curve, tangent), four levels of risk/benefit situations, two levels of speed limit sign, age (two levels), gender (two levels), and traffic (two levels)	Population Average-Generalized Estimating Equations marginal model
16	Xie et al. (2017)	Wuhan University of Technology, China	Average speed, average lane deviation of vehicle and heart rate variability	Performance and Physiological measures	The radius of horizontal curves and slope grade of vertical curves (varied radius and grades)	ANOVA and Root mean square of successive differences
17	Wang et al. (2017)	Tongji University, China	Acceleration and deceleration	Performance	Current segment: curvature, grade, slope type, direction, horizontal type. Adjacent segments: average grade, maximum slope change, the proportion of upslope, number of grade change points, average curvature, maximum curvature, the proportion of right and left turning part, the maximum change in slope, maximum curvature. Considered six levels of adjacent segment length	Random effects multinomial logistic regression model
18	Mecheri et al. (2017)	Paris-Est University, CEREMA Normandie-Centre, France	Lateral position, lateral position variability, and speed	Performance	Lane width (four levels), shoulder width (four levels), traffic condition (with/without)	Repeated ANOVA

Table 3.1: Summary of the selected studies (continued)

ID	Author, year	Institution, country	Measures	Type of measure	Analysed elements	Main method
19	Liu et al. (2016)	Tongji University, China	The standard deviation of the lateral offset and maximum lateral acceleration	Performance	Length of the whole curve, length of the downslope or upslope within the crest or sag segments, average grade on upslope or downslope segments, curvature change rate, radius of the center circular curve, difference between the grades of the adjacent slopes on crest or sag segments, average grade of the upslope or downslope within the crest or sag segments, ratio of what the length of the upslope part to the length of the downslope, and curve direction	Random effects logistic regression models
20	Calvi (2015)	TRE University, Italy	Average driving speed; Pathologic discomfort (takes into account local variability of lateral acceleration); dispersion of trajectory (takes into account the average value of the lateral position and standard deviation)	Performance	Road configuration (category), geometric element (three levels of horizontal curve radius, curve direction, visibility condition (two levels) and transition curve (with, without))	Repeated ANOVA
21	Montella et al. (2015)	University of Naples Federico II, Italy	Operating speed profile	Performance	The radius of the horizontal curve, the radius of the curve preceding the tangent, and length of the curve (same deflection angle)	Piecewise linear regression model
22	Bella (2015)	TRE University, Italy	Local speed (approach and midpoint of the curve) and maximum speed reduction	Performance	Horizontal curve with clothoid with three levels of vertical combination (flat, suggested sag, critical sag)	Repeated MANOVA
23	Zhao et al. (2015)	Beijing University of Technology, China	Average lateral position, eye movement, heart rate	Performance, Physiological, and Subjective measures	Inside shoulder width (five levels)	Repeated ANOVA
24	Oka et al. (2015)	University of Tokyo, Japan	Brain activity (frontal cortex, motor cortex, and the parietal cortex, concentration changes in oxyhemoglobin and deoxyhemoglobin)	Physiological measures	Horizontal curve direction (five identical curves in each direction)	Student's t-test, Two-way ANOVA and MANOVA
25	Qin and Hamdar (2015)	The George Washington University, USA	Average speed and time headway	Performance	The major factors considered included visibility distance (four levels), road friction (two levels), rolling and mountainous terrain (varied horizontal and vertical curve parameters), median existence (three levels), lane width (two levels) and shoulder width (two levels)	Descriptive statistics
26	X. Wang et al. (2014)	Tongji University, China	The average speed differential between the circle curve and approach transition curve; average speed differential between the circle curve and departure transition curve	Performance	Bending Radius, superelevation, and the rate of change of: Circle Curve Slope to Horizontal Curve Slope, to Approach Transition Curve Slope, and to Departure Transition Curve Slope; Circle Curve Length to Horizontal Length, Approach Transition Curve Length, and to Departure Transition Curve Length; and Circle Curve Curvature to Approach Transition Curve Curvature, and to Departure Transition Curve Curvature	Linear regression model

Table 3.1: Summary of the selected studies (continued)

ID	Author, year	Institution, country	Measures	Type of measure	Analysed elements	Main method
27	Bella (2014b)	TRE University, Italy	Local speed (approach and beginning of the curve)	Performance	Horizontal curve with clothoid with three levels of vertical combination (flat, sag, crest) and three levels of the radius (with different deflection angle and approach tangent length)	Two-way repeated MANOVA
28	Ding et al. (2015)	Beijing University of Technology, China	Speed profile and average lane position	Performance	Inside shoulder width (five levels)	Repeated ANOVA
29	P. Wang et al. (2014)	Tongji University, China	Lateral position and speed	Performance	Lane width (four levels) and curve radius (seven levels, varied deflection angles)	ANOVA
30	Bella (2014a)	TRE University, Italy	Maximum operating speed (approaching and midpoint of the tangent) and minimum operating speed (average on the curve and local at the midpoint of the curve)	Performance	Length of approach and departure tangent, length of the horizontal curve, length of clothoids, length of the circular curve, curve radius, longitudinal grade, superelevation, deflection angle, the difference between the radius of the previous curve and that of the actual curve, curvature change rate of the curve	Multiple linear regression
31	Charlton et al. (2014)	University of Waikato, New Zealand	Risk perception	Subjective measure	Curves, visibility, traffic, terrain, lane, signs, straight, bridge, road markings, junctions, banks, weather, shoulder, poles, ditches	Student's t-test and correlation analysis
32	Bella (2013)	TRE University, Italy	Average speed and average lateral position	Performance	Shoulder (with and without), geometric elements (horizontal curve with two radius and different deflection angle, two directions and tangent) and tangents, tree roadside environment (three levels)	MANOVA
33	Ben-Bassat and Shinar (2011)	University of the Negev, Israel	Average speed, average lane position, perceived safe driving speed and estimated road safety	Performance and Subjective measures	Right shoulder width (three levels), and roadway geometry (five levels: horizontal curve with two radii, two directions, and tangent), and guardrail (with/without)	Repeated ANOVA
34	Van Winsum and Godthelp (1996)	TNO Human Factors Research Institute, The Netherlands	Speed, lateral position, steering wheel angle, time to lane crossing and steering error	Performance	Horizontal curve radius (four levels, only left turn direction, same deflection angle)	Repeated ANOVA, correlation and regression analysis

Table 3.2: Characteristics of the experiments

ID	Simulator (DoF)	Simulator Field of View (H x V)	Validation test	Number of drives per participant	Break	Length of consecutive drive	Practical trial length	Final participants	Female	Male	Age mean	Age range	Motion sickness Exclusion	Outlier Exclusion
1	0	NI	NI	5	UN	UN	6 km	22	3	19	38.9	24-62	NA	NA
2	0	130° x NI	RV (ST) ^a	2	10 min	14.44	NI	41	15	26	34.2	20-60	0	NA
3	0	130° x NI	RV (ST) ^a	2	10 min	14.44	10 min	41	15	26	34.2	20-60	NA	NA
4	0	180° x 40°	NI	4	UN	UN	160 sec	24	UN	UN	32.8	20-63	NA	NA
5	NI	NI	NI	16	UN	0.6 km	un-restricted	11	1	10	27.55	22-34	NA	NA
6	0	38° x 25°	NI	4	≤ 5 min	4.5 min	10-15 min	24	8	16	22.6	19-31	NA	NA
7	6	180° x 50°	AV (S)	1	NA	UN	10 min (5 km)	50	17	33	32.2	21-62	4	NA
8	6	180° x 50°	AV (S)	1	NA	32 km	10 min (5 km)	63	19	44	35.4	22-71	5	NA
9	0	110° x 25°	NI	1	NA	4.2 km	20 min	28	14	14	38.86	NI	NA	NA
10	0	NI	N	1	NA	UN	NI	41	NI	NI	NI	NI	NA	NA
11	0	NI	NI	3	24 h	60 km	5-10 min	14	0	14	24	NI	NA	NA
12	8	250° x 40°	N	2	UN	UN	10 min	30	3	27	36.3	24-58	NI	NA
13	NI	NI	NI	UN	UN	UN	un-restricted	20; 24	7; 10	13; 14	36.2; 32.3	20-47; 29-54	NA	NA
14	8	250° x 40°	N	2	≤ 5 min	24 km	10 min	21	4	17	36.5	23-59	NI	NA
15	0	NI	NI	4	UN	30.6 km	4 km	111	49	62	NI	NI	NA	NA
16	NI	NI	NI	1	NA	25 km	10 min	20	5	15	32.9	NI	NA	NA
17	8	250° x 40°	N	2	UN	UN	10 min	21	UN	UN	NI	UN	1	NA
18	0	135° x 56°	RV (ST) ^a	16	≤ 5 min	UN	6.2 km	30	9	21	29.7	20-5	3	NA
19	8	250° x 40°	N	2	UN	24 km	10 min	21	UN	UN	UN	UN	1	NA
20	0	135° x 60°	RV (S)	3	20 min	14.3 km	10 min	30	12	18	26.2	23-35	3	1
21	0	180° x 50°	RV (S) ^a	1	NA	UN	10 min	50	17	33	32.2	21-62	4	NA
22	0	135° x NI	RV (S) ^a	2	≤ 5 min	15 km	10 min	35	13	22	26	23-60	0	NA
23	0	130° x NI	N	1	NA	62.5 km	5-10 min	30	0	30	24	20-26	NA	NA
24	6	120° x NI	NI	2	UN	UN	NI	15	7	8	31.4	NI	0	NA
25	NI	NI	NI	2 or 3	UN	UN	3 min	36	10	26	24.8	20-35	NA	NA
26	8	250° x 40°	N	2	≤ 5 min	24 km	10 min	21	UN	UN	UN	UN	1	NA
27	0	135° x 60°	RV (S) ^a	2	≤ 5 min	15 km	10 min	35	12	23	26	23-62	0	NA
28	0	130° x NI	N	2	UN	62.5 km	5-10 min	30	0	30	24	20-26	NA	NA
29	8	250° x 40°	N	4	30 min	4.9 km	20-30 min	46	20	26	37.6	23-56	0	NA
30	0	135° x NI	RV (S) ^a	1	NA	10 km or 30 km	10 min	131	UN	UN	NI	23-60	4	4
31	0	175° x 41°	NI	1	NA	45 km	3 min	69	38	31	33.7	17-69	NA	NA
32	0	135° x NI	RV (S)	6	≤ 5 min	24 km	8 min	33	7	26	UN	UN	0	3
33	0	140° x NI	AV (S)	3	0	40.2 km	6.4 km	22	11	11	26	23-31	NA	NA
34	0	50° x NI	NI	3	UN	UN	10 min	16	8	8	34	22-47	NA	NA

Note: NI = not informed; UN = unclear; NA = not applicable; S = speed; T = trajectory; N = no; Y = yes; RV/AV = relative and absolute validity; ^a There is a match between the validated measures in Table 3.2 and the studied measures in Table 3.1.

Several studies focused exclusively on geometry features, but nine studies combined geometry and one or more of these factors: drivers' characteristics (age, driving experience), degree of enclosure (roadside trees), traffic, signs, weather, distracting tasks, and risk/benefit situations. Moreover, one study examined the road environment globally regarding drivers' risk perception (Charlton et al. 2014). Considering only the geometric parameters, attributes of horizontal alignment were considered by 30 studies, followed by vertical alignment (13 studies), shoulder width (seven studies), and lane width (four studies). Furthermore, not only the geometry of the current segment was examined, but also eight studies considered the influence of the adjacent segments on driver behaviour.

Overall, they accounted for the effects of road geometry on drivers by measuring performance (speed, acceleration, lateral position), physiological variations (heart rate, brain activity), or subjective aspects (risk perception). To be precise, 25 studies focused only on drivers' performance, and two studies comprised the three cited elements, which indicates low representativeness of interdisciplinary perspectives among studies. Since there are a variety of variables and effects investigated, there is also a variety of statistical methods applied. By and large, studies compared outcomes from different geometries (scenarios) and established associations between variables.

Regarding the factor common to all the research, which was using a driving simulator (see **Table 3.2**), the studies followed a general protocol in relation to the experiments that consisted of three main phases: (i) informing and collecting data from participants, (ii) participants' training in the simulator, and (iii) participants driving the case scenario. From the 34 selected studies, nine experiments were carried out in a driving simulator with six or more degrees of freedom, whilst 21 were conducted in a fixed-base simulator. Four studies did not report this information clearly. The visual field of view ranged from 38°x25° (Horizontal degree x Vertical degree) (Jeong and Liu 2019) to 250°x40° from Tongji University (China), but in general, characteristics of simulators were underreported. Therefore, a detailed description of the equipment and a constant update of the improvements in the simulator systems could be made available through the research centres' websites and be referenced by studies to clarify experiment conditions.

Another topic of interest regarding the equipment is validation. There is the concept of absolute validity when the values obtained in a simulator match those obtained in a real vehicle in absolute terms, and relative validity when the simulator results show the same patterns or effects as real-world driving (Wynne et al. 2019). According to (Törnros 1998), the relative validity is necessary for a driving simulator to be useful as a research tool, while the absolute validity is not essential since research questions usually deal with matters that are related to the effects of independent variables. Among the selected studies, twelve reported the existence of a previous validation test regarding driver speed, trajectory, or both. From those, three claimed to have achieved absolute validity.

Furthermore, an analysis between the studies' measures in **Table 3.1** and the validation test measures in **Table 3.2** reveals that seven studies examined measures that were indeed validated previously in the field, whilst the other five examined measures beyond the validated ones. The matter of validity is not consolidated in the research field, but some authors recommend a validity study for the specific purpose of the research, considering that validity on one measure does not guarantee that other measures will be valid (Allen et al. 2011; Wynne et al. 2019). However, as the authors affirmed, there is still no standardised method for assessing simulator validity.

Indeed, in the characteristics presented in **Table 3.2**, the simulator from Tongji University was considered as not having been validated regarding driver speed or trajectory. However, it was reported that the simulator was validated regarding three other aspects: simulator sickness, stopping distance, and traffic sign size. In this validation test, 75% of the 25 drivers tested should pass for the simulator to be validated (Wang and Wang 2018). Another example is from Bella (2005). In their validity study of driving speed, absolute validity was obtained in nine out of the eleven measurements sites. In the two

points where the speeds in the simulator were significantly higher than those recorded in the field, the road geometry was defined as *non-demanding*, such as long tangents and larger radius curves. This result raises the question of whether there are types of geometry conditions where the simulator is more assertive than others, and whether the validated scenarios should be similar to those studied later. Overall, those examples reinforce that a consensus has not yet been reached in this area.

The minimum length consecutively driven by participants was 0.6 km (Xie et al. 2019), and 62.5 km was the maximum length driven without a break (Ding et al. 2015; Zhao et al. 2015). The interval length allowing participants to rest between driving sessions lasted commonly five minutes or less. It is worth mentioning that, while 24-km-long sessions had breaks of five minutes or less (Bella 2013; Wang and Wang 2018; X. Wang et al. 2014), 30 minutes were given to participants' rest between sessions of 4.9-km-long scenarios (P. Wang et al. 2014).

The number of final participants in the experiments ranged from 11 to 131 individuals. In general, studies did not inform the power of the sample, although the lack of power could explain some of the non-significant results found (Donmez et al. 2006). Gender imbalance is a common characteristic of the studies, in which the male population had more representativeness than the female population. The fact that there is a gender imbalance between the participants does not represent a problem because the most important aspect is that there should be a correspondence between the characteristics of the sample with the characteristics of the population of interest. Furthermore, worldwide figures point out higher male involvement in road traffic mortality (Peden et al. 2004), naturally making this population of greater interest for research.

Three studies analysed only males (Ding et al. 2015; Farahmand and Boroujerdian 2018; Zhao et al. 2015) to form a homogeneous group and minimise between-subjects differences caused by gender. Only one study had more females than males enrolled in the experiment (Charlton et al. 2014). The graph from **Figure 3.2** shows how samples were distributed regarding participants' age based on the typically informed range, mean, and standard deviation. The age mean between studies is 32 years old. It is worth mentioning that since participants' age is not necessarily a variable with a normal distribution, this information does not portray a clear picture of participants' age distribution. Besides, information concerning the initial sample rather than the final sample (after the exclusion of participants) was often reported. Deficiencies in reporting sample characteristics limit the ability to find explanations for different results when comparing studies on the same topic. Participants' features would be better described if a bar chart with frequencies of the final participants in each age-interval were added to the information already provided, allowing sample distribution verification.

Concerning the sample recruitment, although the professional or social background of participants was not usually informed, eight studies stated that participants were affiliated to the university or were connected to it. The requirements for participants' enrollment varied from merely having a driving license to possessing a valid driver's license, and had a cumulative driving distance of at least 10,000 km, an average annual driving distance of at least 3,000 km, no criminal record, nor any record of mental illness or drug use, and no physical conditions such as heart disease or frequent headaches (Chen et al. 2018). However, many studies informed those requirements as a sample characteristic rather than a proper criterion of inclusion. Hence, the reasons for participants' selection were understated. Homogeneity of the sample characteristics (demographic and skill-related) was justified to minimise interferences of those attributes in the experiment (Farahmand and Boroujerdian 2018; Zheng et al. 2018) or to form a representative sample of the drivers' population regarding a specific attribute (gender) (Sadia et al. 2018; Wang and Wang 2018).

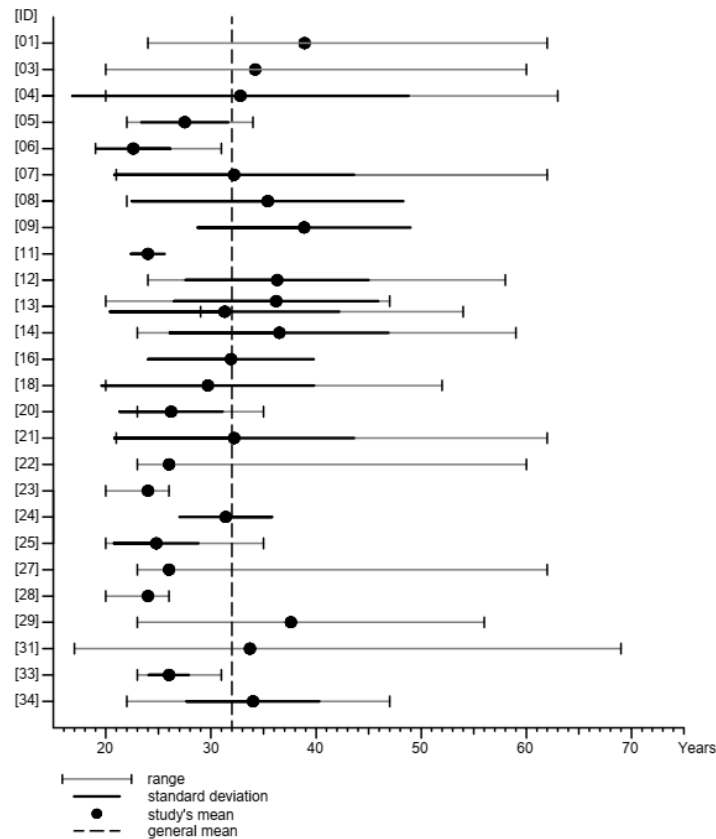


Figure 3.2: Age mean, range, and standard deviation of participants in the selected studies

Two main reasons for participants' exclusion during or after the driving activity were motion sickness and abnormal behaviour (outliers). Nine studies reported the exclusion of participants for the former reason, and three studies imposed an exclusion criterion for outliers. It is important to note that even though motion sickness is a common concern (17 studies mentioned the subject), only ten studies distributed a questionnaire to verify this condition; others excluded participants' results only if they had not completed the entire experiment. On the contrary, the presence of outliers is a concern of just a few studies and was always associated with driving speed. No further investigation was performed by studies to explain the outliers' behaviour, but all studies reported the method and criterion applied to determine them (Bella 2013, 2014a; Calvi 2015).

3.3.3. RISK OF BIAS WITHIN STUDIES

The two highest-rated studies regarding the fulfilment of the experiment items (**Table 3.1**) were Bella (2013) and Bassani et al. (2019a). The studies scored 72% and 70% of the total items, respectively. This score is an outstanding result since the assessment tool of **Table 3.1** includes hard-to-achieve categories, such as the sample representativeness, or not-so-common concerns, such as using a method to assess driver acquaintance with the simulator. Moreover, many studies did not score in an item because no clear mention of the subject was found in the text. However, it cannot be certainly assumed that the authors did not consider that item.

Overall, many potential sources of bias were identified. Using low-level fidelity driving simulators to evaluate complex geometric features or to analyse physiological and subjective outcomes may have affected results by a lack of realism. None of the studies that considered physiological and subjective measures were performed in a high-fidelity driving simulator. Furthermore, limitations arising from the incomplete reporting of driving apparatus and road scenarios prevented a proper assessment of their suitability.

The order effect may not have been considered in all its possible causes. Firstly, the trial test before the actual experiment usually had a pre-specified time, which probably does not ensure proper acquaintance with the simulator for all participants. A method to assess the driver's familiarity with the simulator is still not as well established as it is for the simulator sickness, for example, which is recurrently done through a post-questionnaire. Only two studies (Xie et al. 2019; Zheng et al. 2018) did not fix the time for the practice, and assessment of simulator familiarisation was based on participants' self-reported perception. Indeed, the familiarisation influence and a method for its evaluation still need to be investigated in more detail, above all, because results from the beginning of the driving activity could have been especially affected.

Furthermore, drivers' enhanced familiarity with the environment at the end of the experiment, together with the repetition of the same order of experimental conditions, might have affected the results. If the scenarios are randomly assigned to each of the participants, the potential for confounding factors to be related to the order in which the scenarios are presented reduces, although imbalances can still occur either by chance or due to small sample sizes (McGwin 2011). Therefore, an alternative is to actively counterbalance the scenarios between participants to ensure equal distribution and avoid biases of this sort. Despite that, some studies did not perform a method of randomisation or counterbalance of scenarios or geometries within scenarios. Considering that some studies were a blueprint of a real road, control for this variable is undoubtedly a challenge.

Additionally, it was not possible to state that samples are representative of the drivers' population. None of the studies clearly mentioned a specific target population (for instance, inexperienced young drivers or the elderly), and homogeneous samples by convenience (formed by young male students) were detected. Undoubtedly, the failure of drivers' population representativeness compromises the generalisability of findings. Despite this, the appropriate correspondence between the characteristics of the driver sample and the characteristics of the population of interest is admittedly a difficult gap to fill. The reason for that is partly because information about the target population is not available and partly due to practical and financial difficulties that a statistically representative sample would represent. However, efforts to enrol participants outside university and descriptions of participants' social background are advised to clarify the applicability of the results and comparison between studies.

Regarding the exclusion of participants, two main reasons were identified: experiencing motion sickness and being an outlier regarding outcome measures. Motion sickness is a common issue in simulations, and a good practice performed for various studies was using a questionnaire after the driving activity to identify symptoms of motion sickness. Despite this, many studies did not apply an explicit method for its assessment and reported the exclusion of participant's outcomes only if they did not complete the entire experiment. Hence, participants that did complete the test, but experienced motion sickness may have affected the studies' outcomes. Wynne et al. (2019) warn of the fact that, as the occurrence of simulator sickness is prevalent in some subpopulations, the systematic exclusion of these participants consequently implies that the driver samples will not be representative of the driver population. However, if there is a declared population of interest, drivers that suffered from motion sickness could be replaced by others that also meet the sample requirements.

Contrary to what happens in relation to motion sickness, analysing the presence of outliers received little attention in the driving simulator experiments. The presence of outliers may be due to errors, an indication that participants belong to a different population, or even that they are genuine but extreme values. All studies that assessed outliers evaluated speed measures and discarded participants without further examining the reasons. Looking from the perspective of road safety, they may even deserve a more detailed analysis concerning their characteristics and perceptions, which could help explain their motives, especially for future research guidance.

Table 3.3: Experiment assessment results

ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	
Was driving simulator apparatus suitable for the research intent? (Y/N/NR)	Y	Y	Y	Y	NR	N	Y	Y	Y	NR	NR	Y	NR	Y	NR	NR	Y	Y	Y	N	Y	N	Y	N	NR	Y	N	Y	Y	N	N	Y	Y	Y	
Was a method of randomisation or counterbalance of scenarios performed? (Y/N/NR/NA)	Y	Y	Y	Y	N	Y	NA	NA	NA	NA	Y	NR	Y	Y	NA	NA	NA	Y	NA	Y	NA	Y	Y	NA	Y	NA	Y	Y	NR	NA	NA	Y	Y	NR	
Was a method of randomisation or counterbalance of geometries performed? (Y/N/NR/NA)	NA	Y	Y	Y	NA	Y	NR	Y	NR	NR	NA	NR	NA	NR	N	NR	N	NA	N	N	NR	N	NA	NR	NR	NR	NA	NA	NR	NR	Y	NR	Y	NR	
Was a statistical method of analysis applied? (Y/N)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y		
Does the sample represent the target population? (Y/N)	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	
Was a practical trial performed? (Y/NR)	Y	Y	Y	Y	Y	Y	Y	Y	Y	NR	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	
Was a method to assess driver's familiarisation with the simulator specified? (Y/N/NR/NA)	N	N	N	N	Y	N	N	N	N	NA	N	N	Y	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	N	
Was motion sickness assessed? (Y/NR)	NR	Y	NR	NR	NR	NR	Y	Y	NR	NR	NR	Y	NR	Y	NR	NR	Y	Y	Y	Y	Y	Y	NR	Y	NR	Y	Y	NR	Y	Y	NR	Y	NR	NR	
Was there a clear description of the method to assess motion sickness? (Y/N/NR/NA)	NA	Y	NA	NA	NA	NA	N	Y	NA	NA	NA	N	NA	Y	NA	NA	N	N	N	Y	N	Y	NA	Y	NA	Y	Y	NA	N	Y	NA	Y	NA	NA	
Was the existence of outliers assessed? (Y/NR)	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	Y	NR	NR	NR	NR	NR	NR	NR	NR	NR	Y	NR	Y	NR	NR
Was there a clear description of the method to assess outliers? (Y/N/NR/NA)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Y	NA	NA	NA	NA	NA	NA	NA	NA	NA	Y	NA	Y	NA	NA	
(ΣY/(11-ΣNA)) = %	50	70	55	55	37	44	44	66	37	14	37	40	50	60	25	25	44	55	44	63	44	50	50	44	22	55	55	50	40	60	37	72	55	33	

Note: NR = not reported; NA = not applicable; N = no; Y = yes.

3.3.4. SYNTHESIS OF THE STUDIES' RESULTS

The data synthesis compiles the evidence obtained by studies on the effects of road geometry on drivers' performance divided into the five main topics: horizontal curve, transition curves, shoulder width, lane width, and vertical alignment. An important finding of this review is the high heterogeneity between studies. There is a diversity of scenarios – that diverge in the number of lanes, lane width, shoulder, tangent length between curves, curves length, longitudinal grades, the presence or not of transitions curves – combined with a diversity of outcome measures – the speed at the beginning of the curve, average speed, speed in the middle of the curve, maximum or minimum speed on the curve – that prevented synthesising the results of the studies without losing much information. Despite that, for horizontal curve radius, shoulder width, and lane width, a relative homogeneity in studies allowed a summary of the findings, presented in **Tables 3.4, 3.5** and **3.6**, although it is limited to observed trends (increase/decrease). They are presented based on their score in the assessment tool, from the highest score to the lowest.

The next sections focus on a detailed presentation of the studies' findings and analysis of their potential contribution to the road safety knowledge gaps.

3.3.4.1. Horizontal Curve

3.3.4.1.1. Findings of the Studies

Most of the studies considered the effects of the horizontal curve radius on drivers' objective measures. Studies covered a broad range of radii – between 15 m to 3,000 m – albeit studies on lower radii were rare (see **Table 3.4**). Regarding drivers' speed, studies' results were consistent in reporting that drivers adapted and reduced their speed on sharp curves (Bella 2013; Bassani et al. 2019a; Calvi 2015; Bella 2014b; Ben-Bassat and Shinar 2011; Montella et al. 2015; P. Wang et al. 2014; Xie et al. 2019; Van Winsum and Godthelp 1996; Xie et al. 2017).

Table 3.4: Summary of main findings for horizontal curve radius increment

ID	Radius range (m)	Speed related measures	Lateral position related measures	Experiment items
32	200 - 400	↑	↓	72%
2	120 - 430	↑	NA	70%
20	200 - 1000	↑	∇	63%
4	204-350	NA	↓	55%
27	250 - 600	↑	NA	55%
19	NI	NA	∇	44%
33	80 - 380	↑	∇	55%
6	100 - 800	NA	↓	44%
21	125 - 800	↑	NA	44%
29	15 - 200	↑	∇	40%
12	400 - ∞	NA	↓	40%
5	300 - 2400	↑	↓	37%
34	40 - 160	↑	NA	33%
16	630 - 3000	↑	∇	25%

Note: ↑ = increased; ↓ = decreased; ∇ mixed results; – = non-significant.

NA = not applicable.

The study conducted by Montella et al. (2015) suggested that for sharp curves, drivers still had to adjust their speed while driving on the curve. The authors noted that, on sharp curves, deceleration ended close to the curve centre, and acceleration started close to the curve end. In contrast, in larger radii, the endpoint of deceleration moved towards the curve beginning, and the beginning of the acceleration moved towards the curve centre.

Similarly, the drivers' lateral position was also investigated by several studies, usually in terms of lateral displacement, considering a reference point (centre of the traffic lane, lane edge, or road axis), but also in terms of the standard deviation of this measure. Bella (2013) studied scenarios considering guardrails, shoulder, and geometry (right/left sharp/shallow curves and tangents) and found values of lateral position statistically different from each other regarding the geometry variable. The highest values were observed almost always on sharp curves. The exception was the scenario with no guardrail but with a 1.5 m shoulder, where the highest values were on right curves, sharp and shallow.

Bassani et al. (2019a) studied the influence of the available sight distance on drivers' trajectory, simulating a wall in the inner part of the curve. An interesting point in this paper is that they analysed the standardised dispersion of trajectory (a variable that evaluates the ability of the driver to select an appropriate steering angle throughout the curve). The authors reported a significant influence of the radius and the direction of the curve on drivers' trajectory. The accuracy of the trajectory increased for greater radii, and leftward curves.

Ben-Bassat and Shinar (2011) reported no significant main effect for roadway geometry on lateral positions (measured in meters from the concrete Jersey barrier), but a significant interaction between roadway geometry and guardrail existence. In the presence of the guardrail, drivers moved in the opposite direction; however, on the sharp left curves, the lateral position was more affected than in the other scenarios since on the sharp left curves, without the guardrail, drivers positioned themselves closer to the edge line. When considering the standard deviation of the lateral position, a main effect for road geometry was found where values were significantly higher on sharp curves than on shallow ones.

Calvi (2015) found significant differences in the Dispersion of Trajectory (DT – a measure that considers the average value of the lateral position and the standard deviation) between curves with different radii. However, this was influenced by the direction of the curve: for the right curves, the smaller the radius, the lower the DT, whereas for left curves, differences were not significant.

Chen et al. (2018) observed no influence of the curve direction on lane departure to both inside or outside the curves, with radii ranging from straight segments to 400 m (or curvatures from 0 to 2.5 m/km), while Mauriello et al. (2018) stated that, in general, drivers drove closer to the centerline (and in the opposite lane) on the left curves more often. However, the effect of the curve direction was significant only for half of the studied radii.

P. Wang et al. (2014) and Xie et al. (2017), although studying very different ranges of radii (15 m to 200 m and 630 m to 2,400 m), found a similar trend in lane deviation. In the lowest values of radii, lane deviation tended to increase with an increasing radius. After that, a reverse trend was observed, where lane deviation tended to decrease with an increasing radius. Xie et al. (2017) also found a higher lane deviation range in both the smallest and largest radii studied.

Moreover, other studies that addressed the influence of horizontal curves to some extent indicated that an increase in the radius tends to decrease the lane departure (Chen et al. 2018), decrease the mean and standard deviation of lane deviation (Xie et al. 2019), decrease steering errors (Van

Winsum and Godthelp 1996), and decrease the standard deviation of lateral position and standard deviation of the steering wheel angle (Jeong and Liu 2019).

Finally, the study of Farahmand and Boroujerdian (2018) is worth to mention since they not considered the individual horizontal curves but tested three different levels of curved roads classified into three categories by their cumulative delta angle (low, moderate, and high road design variability). They recorded drivers' steering wheel movements, the standard deviation of steering wheel movements, and lane positioning ability. Only lane positioning ability data showed significant differences between scenarios, with a performance improvement for scenarios with moderate and high geometric variety. Differences in the other two measures were not statistically significant.

3.3.4.1.2. Road Safety Perspective

From the road safety perspective, a smaller curve radius is associated with an increased risk of crashes (Elvik 2013; Papadimitriou et al. 2019). However, Elvik (2013) pointed out significant differences between countries related to the prediction of accidents for radii smaller than 200 m. Furthermore, combinations of geometry conditions with sharper curves are also taken as risk increasing factors – such as long straight sections or gentler curves, and sharp vertical sag or sharp crest curves. Opposed to that, some combinations were associated with a decreasing risk, such as high frequency of curves, although it is not clear if it is related or not with the different traffic volumes between roads, generally lower on tortuous roads (Papadimitriou et al. 2019; Elvik 2019). In the Infrastructure Risk Rating Manual for Australian Roads (Zia et al. 2019), aspects of horizontal alignment are taken into account through a variable that considers the degrees of turn per km calculated by summing the deviation angles of the horizontal curves and dividing by the road length. However, in the manual, higher values of this measure are associated with a higher risk of accidents.

In general, driving simulator studies included in this review did not focus enough on these subjects (small radii, frequency of curves, or the influence of the entire road alignment on the results of the driver behaviour on a particular curve) to add a substantial contribution to their enlightenment. Furthermore, driving simulator studies reproduced a gap found in the literature about the effects of the deflection angle, which is typically not considered in association with the radius. In The Handbook of Safety Measures (Elvik et al. 2009), the authors highlight that the literature is inconsistent as to whether or not the relationship between the radius and accident rate depends on the deflection angle.

Despite that, driving simulator studies were consistent in indicating that drivers adjusted their behaviour as the radius became smaller, decreasing their speed, which is actually associated with lower risks of accidents (Nilsson 2004). Thus, the chosen speed might be just sufficient to negotiate the curve, but not without invading the opposite lane, going closer to the edge of the road, or weaving; performances that could be associated with the risk of a frontal collision, run-off-road accidents or vehicle loss of control. Indeed, some studies reported higher values of lateral position and standard deviation of lateral position on sharp radii; however, these measures seem to be influenced by other variables (traffic, shoulder, guardrail).

As an example, focusing specifically on the lateral position at the curve centre and considering the cutting manoeuvre: on right curves, drivers are on the inner lane of the road and are constrained by the edge of the road, whilst on left curves, they are on the outer lane and can skip towards the opposite lane if they wish. Hence, the presence of opposing traffic, shoulders, and guardrails affect right and left curves differently, overlapping with radius effects. Therefore, a separate analysis of left and right curves might be advisable since the position of the driver in different traffic lanes imposes distinct constraints and motivations.

Finally, when the results were not evaluated in a few isolated curves, but considering the alignment as a whole, higher headway time and higher lane positioning ability were observed in mountainous terrain. This seems to corroborate the idea of drivers adopting safer behaviour in environments with a high frequency of curves; however, more studies that focus specifically on this perspective are needed.

3.3.4.2. Transition Curves

3.3.4.2.1. Findings of the Studies

The high rated study in this subject, according to **Table 3.3**, was Calvi (2015). The author studied two scenarios: with and without clothoid, each one with three levels of radii (200, 500, and 1,000 m) and observed that the average speed on curves with clothoid was higher than on curves where the clothoid was not present. The Pathological Discomfort (PD – a measure that considers local variability of lateral acceleration) on curves with the transition was significantly lower than those recorded on curves without transition, although this was not revealed on shallow curves (1,000 m). Furthermore, the Dispersion of Trajectory (DT – a measure that considers the average value of the lateral position and standard deviation) recorded on curves with the clothoid was significantly lower than on curves without the transition element. Montella et al. (2018) also found similar results regarding the lateral position and lateral position variability. The most considerable differences in trajectory dispersion were observed on the curve approach (i.e., on the tangent and clothoid segment before the circular curve). Moreover, with respect to the three levels of deflection angle analysed (20, 40, and 60 degrees), they reported that the positive effect on the dispersion of trajectory was smaller on curves with small deflection angles.

Wang and Wang (2018) and X. Wang et al. (2014) reported the influence of the length of the transition curve. The first study investigated four combined (vertical and horizontal) curves and declared that only for sag-combinations, an increase in the length of approach transition curves increased the probability of a substantial change in speed (decrease/increase) measured as the difference between the maximum and minimum speeds reached on the entire curve (transition and circle curve). The second study found a reduced speed differential between the circle curve and the transition curve associated with the increasing length of the latter. They stated that a sufficient length of the transition curves would make drivers adapt to the alignment and accelerate.

3.3.4.2.2. Road Safety Perspective

The results previously presented are in accordance with the literature, which indicates that the length of the transition curve must be controlled. Excessively long spirals can mislead drivers about the sharpness of the impending curve, while too short spirals result in relatively large levels of peak lateral acceleration (Bonneson et al. 2000; American Association of State Highway and Transportation Officials 2018).

Therefore, a maximum limiting radius is indicated based on the lateral acceleration rate. Only radii below this maximum are likely to obtain safety and operational benefits from the use of transition curves, which for a 100 km/h speed is at around 600 m (American Association of State Highway and Transportation Officials 2018). The driving simulator studies points out that not only the radius influenced results on this variable, but also the deflection angle.

3.3.4.3. Shoulder Width

3.3.4.3.1. Findings of the Studies

Six studies analysed the impact of the shoulder width on drivers' performance. Bella (2013) is the study with the highest score in **Table 3.3**. The author considered scenarios with 1.5 m shoulder and without a shoulder. Results showed that in the presence of a shoulder on the right side, drivers

adopted higher speeds. However, other studies did not find differences in drivers' speed (Mecheri et al. 2017; Ding et al. 2015; Ben-Bassat and Shinar 2011).

Furthermore, Bella (2013) reported that the shoulder induced drivers to choose a lateral position further from the road axis and to the shoulder. This conclusion is in line with other studies' findings. Mecheri et al. (2017) observed that even external shoulders of 0.5 m wide had modified how drivers positioned themselves, and Ben-Bassat and Shinar (2011) reported that not only participants drove closer to the shoulder, but there was a difference in the lateral position between the 0.5 m shoulder scenario and the two other scenarios (1.2 or 3.0 m).

Mecheri et al. (2017) considered external shoulder widths from 0 to 0.75 m and found no differences in the variability of lateral position between them. However, on the study of internal shoulder width, Zhao et al. (2015) found substantial differences in the variability of the lateral position occurring when comparing the scenarios when the shoulder was present (0.5 and 2.5 m) with the scenario in the absence of shoulder. In the latter condition, values were lower. A summary of the main findings of all the studies on this topic is presented in **Table 3.5**.

Table 3.5: Summary of main findings for shoulder width increment

ID	Width range (m)	Speed related measures	Lateral position	Experiment items
32	0.00 - 1.50	↑	to the shoulder	72%
18	0.00 - 0.75	–	to the shoulder	55%
23 and 28 ^a	0.00 - 2.50	–	to the shoulder	50%
33	0.50 - 3.00	–	to the shoulder	55%

Note: ↑ = increased; – = non-significant.

^aInside shoulder

3.3.4.3.2. Road Safety Perspective

The safety effects of shoulders are somewhat inconsistent in the literature. The presence of shoulders is associated with a reduction in some types of crashes (such as run-off-road or head-on collision), while it may increase others (speed-related crashes or stopped-on-shoulder vehicles/manoeuvres) (Filtness and Papadimitriou 2016; Srinivasan et al. 2009). Bamzai et al. (2011) pointed out a probable benchmark for the shoulder width regarding safety: shoulders below 2.44 m were found to reduce shoulder-related crashes (although with considerably large variations between studies), while shoulders up to 2.44 m may increase shoulder-related crashes, especially severe ones.

The results from the driving simulator studies agree that shoulders would reduce head-on collision since drivers tend to drive farther from the opposite lane traffic. However, only one study corroborated with the idea of shoulder influencing speed, and consequently, speed-related crashes, although it was the high rated study on the experiment assessment tool (see **Table 3.3**). Furthermore, studies did not seek to confirm a benchmark of shoulder width in terms of speed or lateral position, adopting typical variations of the shoulder width in their experiments.

3.3.4.4. Lane Width

3.3.4.4.1. Findings of the Studies

Three studies investigated the effects of lane width on driver performance. Among them, Mecheri et al. (2017) was the highest scored study in **Table 3.3**. The authors reported that lane narrowing affected the vehicle position towards the edge line significantly, but only in the absence of oncoming traffic since, in the presence of other vehicles in the opposite lane, drivers positioned

themselves towards the edge line regardless of the lane width. Moreover, drivers swerved less as the lane width decreased.

P. Wang et al. (2014) also found lower lateral position deviations in narrow lanes, but contrary to Mecheri et al. (2017), who found no difference in the participants' driving speed, they reported statistically significant differences with higher speeds observed on wider lanes. However, they stated that the influence on speed was less significant than on lateral position. Qin and Hamdar (2015) also found that participants tend to choose higher speeds when travelling on wider lanes. The main findings of all the studies on this topic are summarised in **Table 3.6**.

Table 3.6: Summary of main findings for lane width increment

ID	Width range (m)	Speed related measures	Lateral position deviation	Experiment items
18	2.75 - 3.50	–	↑	55%
29	2.70 - 3.50	↑	↑	40%
25	2.75 - 3.00	↑	NA	22%

Note: ↑ = increased; – = non-significant; NA = not applicable.

3.3.4.4.2. Road Safety Perspective

Considering the safety effects in relation to lane width found in the literature, according to Filtness and Papadimitriou (2016), who considered the impact of narrow lanes for varying amounts of annual average daily traffic (AADT), a high traffic volume combined with narrow lanes has resulted in a negative effect on the safety of road users. In contrast, in low traffic volume, they resulted in a positive impact, which is in line with the findings of driving simulator studies.

However, Hauer (2000) reported a decreasing trend in accident rates when widening lanes for all accidents, at least until some point, that for the author would be at around 3.35 m, meaning that lane widths beyond 3.65 m may be to the detriment of safety. Considering that, driving simulator studies do not add much since the range of lane width investigated were below 3.65 m.

3.3.4.5. Vertical Alignment

3.3.4.5.1. Findings of the Studies

Many studies considered aspects of the vertical alignment, such as the presence of sag and crest curves and longitudinal grade variation, but combinations of those elements with horizontal curves were a recurrent subject.

Bella (2014b) examined sag and crest curves combined with horizontal curves. The author stated that the speed at a point 200 m before the curve was not affected by the type of the curve (crest/sag). In contrast, the speed at the beginning of the crest curves was significantly less than that on the reference curves (horizontal curves with a flat approach tangent). No significant difference in speed was found for sag curves.

Wang and Wang (2018) also studied combined horizontal and vertical curves. The authors reported that for sag curves drivers were more likely to maintain their speed as the slope differential of maximum and minimum slope increased, while for crest curves, as the k-value increased (k represents the horizontal distance along which a 1% change in grade occurs on the vertical curve), the probability of a substantial speed reduction also increased. Furthermore, the authors studied upslopes and downslopes and observed that, on downslope curves, as the slope became steep, drivers were more likely to increase their speed. For upslope curves, they found that as the following segment became steeper (either upslope or downslope), drivers were more likely to maintain their speed. In a different study but with the same scenarios, Wang et al. (2017)

reported that acceleration was more likely to occur on downslopes and less likely to occur on upslopes.

On the contrary, Sadia et al. (2018) studied the influence of vertical alignment on drivers' speed variation but considering vertical curves (sag and crest) individually, that is, not combined with horizontal curves. Participants were divided into four groups based on their age (young/old) and gender (male/female). The authors reported that vertical sag curves had significant effects only on women, leading to higher speeds, while the only significant effect of vertical crest curves was for younger men, who raised their speeds.

Furthermore, not only speed-related measures were analysed, but also the effects on the lateral offset of combined curves were investigated. Liu et al. (2016) found that the grade was statistically significant only for sag curve combinations, where the standard deviation of the lateral offset had a positive correlation with grade values. In the study carried out by Chen et al. (2018), when vertical grades were divided into three grade categories ($<-2\%$, from -2 to 2% , and $>2\%$), lane departure was found to be significantly less in downward and upward slopes when compared with the flat category. However, no significant differences were found in the speed between the three categories.

Xie et al. (2019) considered four scenarios regarding grades (-0.5% , -2.5% , -4.5% and -5.5%). The slope grade was found significant for average speed but not for lane deviation, although there was no significant correlation between slope grade and speed or lane deviation. Xie et al. (2017) pointed out that the influence of slope grade on average speed and lane deviation was not found to be statistically significant. Longitudinal grades varied from -0.9% to -3.8% .

3.3.4.5.2. Road Safety Perspective

The relevance of the horizontal curve radius also has repercussions in the studies of vertical alignment as they were usually analysed in combination. Regarding the influence of vertical alignment on road safety, steep slopes are associated with greater risks of collision, but the exact extent of the effects is not yet clear (Elvik et al. 2009; Papadimitriou et al. 2019). Bauer and Harwood (2013) discriminated types of vertical curves into two categories: when there is a reversal of the slope grade (type 1 crest and sag) and when the previous and the subsequent grades are both positive or negative slopes (type 2 crest and sag). Authors reported differences between accident risks associated with them: for type 1 crest and sag, the crash frequency rose with increased grade difference, while for type 2 crest and sag, the crash frequency was not influenced by the vertical alignment. However, regarding the ramps (straight grades), steeper grades increased crash frequency.

Driving simulator studies did not examine vertical curves particularly regarding differences between subsequent slope grades but considering only the previous slope grade. The differences between type 1 crest and sag revealed by driving simulator studies seem to be related to visibility constraints on crest curves resulting in lower speeds, although risk groups (young men) might raise their speeds in such situations. The lateral position had mixed results, and more studies are needed before any conclusion can be pointed out.

3.4. CONCLUSIONS

This systematic review pored over 34 driving simulator studies on the effects of road geometry on driver behaviour. Studies analysed mainly horizontal alignment (especially horizontal curve radius, but also curve direction, transition curves, and curve length/angle), vertical alignment (grade and vertical curves), and cross-section characteristics (shoulder and lane width). The main conclusions of this paper are summarised as follows:

- The horizontal curve was the leading researched topic. Speed related measures have shown a more direct relationship with the radius of the curve than lateral position measures, suggesting that other factors significantly affected drivers' behaviour in the second case.
- While the studies on the effects of shoulder and lane width on drivers' behaviour converged in their results, studies that considered the radius of the horizontal curve showed some discrepancies. A possible reason for this is that, when examining horizontal curves, other variables intrinsically related to the curve (such as deflection angle, presence/absence of transition curves, and direction of the curve) may have influenced the differences found among studies' results. However, many studies did not report or explored those other characteristics. On the other hand, research focused on shoulders or traffic lanes were concerned only with the width variable. Therefore, the scenarios tested by studies were probably more similar to each other, contributing to the homogeneity found in the studies' results on this subject.
- The highest-rated study concerning the driving experiment (Bella 2013) was able to detect minor effects regarding drivers' speed that others did not find when studying shoulder influence.
- This paper highlighted the current practice regarding driving simulator experiments analysing road geometry features, which revealed potential sources of bias, as well as typical deficiencies in reporting. Suggestions were made for improving the experiments, which can also be useful for other types of driving simulator studies.
- Many of the studies were case-oriented, focusing on a specific road, occasionally not making use of the manipulation of variables allowed by the simulated environment. Thus, this paper pointed out gaps in the road safety knowledge where the potential of driving simulators could be applied in the development of future research.

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4

A NOVEL APPROACH TO SET DRIVING SIMULATOR EXPERIMENTS BASED ON TRAFFIC CRASH DATA

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Accident Analysis & Prevention

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"The number of road traffic deaths continues to climb, reaching a high of 1.35 million in 2016."
(WHO, 2018, p. 4)

The third paper originated from a recurring argument that has been mentioned in the first paragraph of many road safety studies, in particular in the studies included in the previously presented systematic review. Indeed, the number of injured or killed people in the traffic system is alarmingly high; however, no driving simulator study developed their analysis using a formal method directly considering a crash database.

Therefore, the third paper was intended to take full advantage of the traffic crash data, road inventory, and traffic volume counts available for this thesis' development. The paper focused on problems regarding the definition of the simulated scenarios and drivers' recruitment to participate in the driving simulator experiments.

The proposed framework was based on Clustering Analysis, where a balance between homogeneity within the clusters and diversity of scenarios was sought to reduce the diversity of crash data into a set of test scenarios. The framework can be seen as an alternative to support the definition of driving simulator experiments considering real situations.

In this paper, only single-vehicle loss-of-control crashes were included in the analysis, considering that road geometry and its interaction with driver behavior had potentially played a significant role. The database had rich enough information regarding road geometry to achieve satisfactory results. In the end, the outcomes from this paper served as input to the driving simulator experiment (chapter 7).

ABSTRACT

Several studies have often cited crash occurrences as a motivation to perform a driving simulator experiment and test driver behavior to understand their causal relations. However, decisions regarding the simulated scenario and participants' requirements do not often rely directly on traffic crash data. To fill the gap between simulation and real data, we have proposed a new framework based on Clustering Analysis (K-medoids) to support the definition of driving simulator experiments when the purpose is to investigate the driver behavior under real risky road conditions to improve road safety. The suggested approach was tested with data from three years of police records regarding loss-of-control crashes and information on three Brazilian rural highways' geometry and traffic volume. The results showed the good suitability of the method to compile the data's diversity into four clusters, representing and summarizing the crashes' main characteristics in the region of study. Drivers' attributes (age and gender) were initially intended to integrate the clustering analysis; however, due to the sample's homogeneity of these characteristics, they did not contribute to the cluster definition. Hence, they were used simply to identify the target population for all scenarios. Therefore, we concluded that driving simulator experiments could benefit from the new approach since it identifies scenarios characterized by many variables connected to real risky situations and orients participants' recruitment leading to efficient safety analysis.

KEYWORDS: Driving Simulator Experiment; Clustering Analysis; Scenario Development; Road Safety

4.1. INTRODUCTION

The use of driving simulators in road safety research has dramatically increased since the beginning of the 2000s. Indeed, the advantage of manipulating scenarios and confounding variables added to the repetitive reproduction of the same conditions for each participant without engagement in dangerous activities made it an invaluable asset to address a wide range of questions. In the present study, the focus is on using driving simulators to evaluate road risk factors based on real crash data to propose safety improvements. In this context, the simulation research is particularly interesting to confirm causal associations inferred in the crash data analysis.

Arguably, there are some drawbacks regarding driving simulators, particularly for road design analysis, as discussed by Granda et al. (2011). An important one is that drivers cannot fully experience the vehicle dynamics associated with complex roadway geometries. Indeed, the authors argue that some motion should be considered when studying new geometric designs; however, mid-level simulators may still provide valid results for analyzing complex geometries or evaluating signs, depending on the variables investigated. Another drawback is regarding the prevalence of simulator sickness, which complex geometries can impose on participants. In this case, the authors highlight that simplifying the roadway's geometry is not an option, but strategies such as the participants' graduate training can reduce this problem.

Furthermore, another topic that should be considered when using driving simulators to analyze drivers' behavior is validation. According to Törnros (1998), relative validity should be guaranteed for a driving simulator to be useful as a research tool, while absolute validity would not be essential since research questions are usually related to the effects of independent variables. Wynne et al. (2019) define relative validity when the simulator results show the same patterns or effects as real-world driving, and absolute validity when the values obtained in a simulator match those obtained in a real vehicle in absolute terms. Although there is still no standardized method for assessing simulator validity, several validation studies have shown that driving simulators have achieved the needed relative or even absolute validity (Allen et al., 2011; Hussain et al., 2019; Wynne et al., 2019).

Thus, after considering the appropriateness of using a driving simulator for the research purpose, typical concerns regarding the experiment are related to the scenarios' definition and drivers' requirements to participate in the study. Following the Safe System Approach (Reason, 2008; Wegman et al., 2008) principles, this paper considers the combination of factors that eventually impacted crash occurrences, mainly focusing on road risk factors.

Traditionally, studies have defined the risky conditions based on their expertise, selecting the most frequent crash conditions, using a blueprint of an existent road, or proposing a factorial design (Chen et al., 2019; Chen et al., 2018; Chrysler et al., 2015; Xie et al., 2017; Yang et al., 2009; Fleury and Brenac, 2001). However, there are some drawbacks to those approaches.

First, relying on expertise implies having a measure of unwanted dependence on the groups' interpretation on the scenarios' selection. On the other hand, choosing the most frequent crash conditions might not be feasible, considering the typical databases that characterize crash occurrences, which have many variables and categories. Therefore, this strategy could result in several combinations with relatively low frequency as the most frequent ones. Next, studying a blueprint of a real road could bring the disadvantage of making participants drive long sessions throughout the entire road alignment, not focusing on the segments where the safety problems indeed occur. Lastly, studies that adopted a factorial design might have focused on rare conditions, not based on a real safety problem. Considering one of the most studied subjects on driving simulators about road geometry's effects on drivers' performance, the radius of the horizontal

curves, a factorial design will propose, for example, four levels of radius covering a specific range of values. However, how typical is it to find a curve with a 1000-meters radius and a central angle of 180° on a rural road with no shoulder combined with a flat terrain? Therefore, although the factorial design helps understand the safety problems and solutions, real conditions should be considered for baseline scenarios.

Similarly, considering the participants' recruitment, a common approach for choosing participants for driving experiments is convenience sampling (Bélanger et al., 2015; Wynne et al., 2019). However, this could be a strong source of bias in the research, compromising its validity. Not rarely, in driving simulator studies, many of the participants are affiliated or connected to the university or research center where the experiment is taken place (Calvi, 2015; Farahmand and Boroujerdian, 2018; Kang et al., 2019). Therefore, a better approach would be to identify a target population and make an effort to enroll participants who meet the predefined criteria.

Regarding the safety problems on existing roads, information about the active driving population might not be available; however, an alternative is to consider the characteristics of the drivers involved in the crashes. Arguably, the appropriate similarity between participants and the target population is hard to achieve since a statistically representative sample imposes practical and financial difficulties. However, identifying some features of the drivers involved in the crashes and including participants with those characteristics may provide a better understanding of the real safety problems and their solutions.

Therefore, this study aims to propose a consistent and feasible approach based on traffic crash data, road inventory, and traffic volume counts to support the decisions regarding the scenarios' conception and sample characteristics for driving simulator experiments when the purpose of the study is to understand the driver behavior facing real road risk factors. The proposed framework follows the methodology developed to define test scenarios for evaluating vehicle safety systems for computer simulations that applied clustering analysis for this purpose. Therefore, studies on this topic are presented in **Section 4.2**. In **Section 4.3**, the proposed approach is explained, followed by the data's description in **Section 4.4**, which was used as an example of the proposed framework's potential. Afterward, the results are provided in **Section 4.5**, and in a separate section, they are discussed (**Section 4.6**). Finally, the last section, **Section 4.7**, presents the main conclusions.

4.2. BACKGROUND

Several methods could be regarded in the analysis of crashes (Lord and Mannering, 2010); however, Clustering Analysis (CA) has been proposed and applied successfully to identify patterns considering the typical nature of the crash datasets, characterized by high-dimensionality and diversity of variables. Regarding the analysis of road factors on safety, a common approach is to cluster the data into relatively homogeneous groups and then develop a model for each cluster. This approach usually aims to identify the cluster's unique, influential factors (Chang et al., 2019; de Oña et al., 2013; Li et al., 2019; Sun et al., 2019; Taamneh et al., 2017). Typical information explored in those studies is the sex and age of the drivers, information related to the crash cause, passenger presence, type of maneuver before the crash, type of vehicle, type of road, weather conditions, season, visibility, lighting conditions, day of the week, time of the day, injury severity, crash type, among others.

The vehicle safety research field has also been taking advantage of CA, although with diverse data. Studies in this field have applied CA to define base scenarios for computer simulations. For instance, hierarchical clustering analysis was used to group run-off-road crashes from a German database to provide a basis for test scenarios (Nilsson et al., 2018). The database contained

variables of initial speed, departure angle, initial lateral distance from the vehicle center to the road edge, class of road, lateral acceleration at the posted speed, lighting conditions, road surface conditions, and loss-of-control status. In this study, nine separate groups were selected from the initial thirteen clusters formed, and their characteristics were considered in the scenarios' development.

In another study, clustering methods were examined to define intersection scenarios for assessing automated safety systems for vehicles (Sander and Lubbe, 2018). The authors used the same database of German crashes but investigated three clustering methods: Hierarchical Clustering (HC), Partitioning Around Medoids (PAM), and Latent Class Clustering (LCC). They considered nine variables for the CA, three of them quantitative: initial speeds (both cars) and collision angle, and six qualitative: light conditions, sight obstructions (both vehicles), precipitation, and impact areas (both vehicles). However, in the end, the authors concluded that it was not possible to reduce the diversity of intersection crashes into a set of test scenarios.

Another example of CA to form test scenarios for vehicle safety systems described car-to-two-wheeled crashes (Sui et al., 2019). The authors informed that they used the PAM algorithm for partitioning the crashes considering five nominal variables: time of the crash, visual obstruction, the pre-crash driving behavior of the car driver, the pre-crash driving behavior of the two-wheeled driver, and the relative moving direction between the car and the two-wheeled before the crash. The authors decided on the segmentation into six different clusters, balancing a high average silhouette width and the clusters' size. This study's distinct mark was that the authors could compare the scenarios formed by the clusters' medoids and the ten most frequent scenes formed by all possible combinations among variables' categories since the number of variables and categories was limited. In doing this, they found that the clusters' medoids did not represent just four of the ten most frequent combinations. At this point, it is important to note that this type of frequency analysis applied to a high-dimensional dataset constituted of many variables and categories would not be significant since, most likely, several combinations with relatively low frequency would tie first.

Finally, one of CA's most evident applications to form test scenarios was used in a British database and was interested in pedestrian crashes to develop autonomous emergency braking systems (Lenard et al., 2014). The authors chose hierarchical clustering to establish a base scenario derived from the predominant categories identified in the largest cluster. Afterward, they created other scenarios varying some characteristics of the base scenario depending on the other clusters' results. However, they acknowledged an element of judgment involved in the stage of scenarios' development.

Summing up, CA has been used with typical traffic crash databases, usually with the intention of model development afterward. Considering this application, they showed significant improvement to the clusters' models compared to the whole-data models, uncovering otherwise hidden relationships. On the other hand, some studies applied CA to define test scenarios to develop vehicle safety systems. Variables used in those analyses differ from the usual variables of traffic crash databases, and results were sometimes not completely satisfactory. Therefore, we propose a novel framework supported by CA to define scenarios and participant samples for driving simulation experiments based on real crash data to study crash dynamics and improve prevention strategies.

4.3. METHODS

The framework proposed in this study to support the rationale of driving simulator experiments is represented in **Figure 4.1**. In the flowchart, the identification of the scenarios to be designed

and the participants to be selected for the experiments rely on the traffic crash database, road inventory information, and traffic volume counts. They will be employed to identify relevant patterns to be investigated, combinations of risky situations, and drivers' characteristics. These patterns are defined using the clustering analysis, which is the focus of the current study, and it will be shown and discussed in the next subsection. After these steps, the experiment can be conducted considering the participants that fit the drivers' features associated with each scenario.

Next, the data collected during the experiments can be analyzed to investigate the driver's behavior. The analysis of typical surrogate measures could confirm risky behaviors in these scenarios, enlighten how drivers interpret and react to the environment, and support safety improvements. Therefore, the researchers may decide to explore the risky situations further and, thus, continue the study by creating new scenarios to compare with the base one, finishing with the identification of tailored solutions.

It should be noted that this general framework can be adjusted to cover other types of research, such as the analysis of a specific type of crash or comparison between drivers' samples. If this is the case, the database needs to be verified and treated accordingly, and the clustering analysis may also be fitted to meet the new objective.

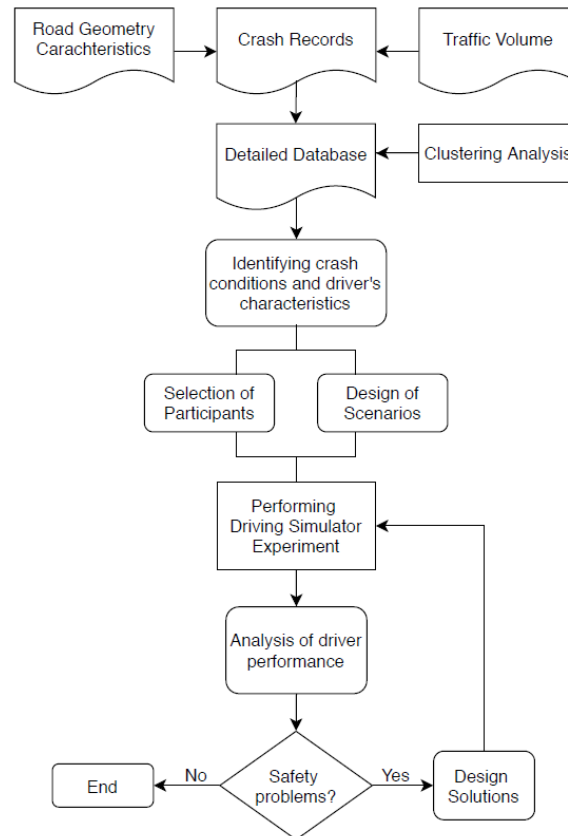


Figure 4.1: Flowchart of the proposed framework

4.3.1. CLUSTERING ANALYSIS

Clustering Analysis (CA) intends to classify cases into similar significant groups based on their variables' categories. For this purpose, several clustering approaches have been developed. Although there is no best clustering technique, good partitions are obtained when there is a good correspondence between the model and the data (Jain, 2010).

The most typical clustering algorithms are broadly classified into two groups: hierarchical and partitional. Hierarchical clustering algorithms recursively partition each cluster into small subclusters (divisive mode) or combine them into superclusters (agglomerative mode). Conversely, partitional clustering algorithms find all the groups simultaneously as partitions of the data and do not impose a hierarchical structure (Jain, 2010).

Both the Hierarchical and the Partitional approaches can be used considering any distance measure derived from the matrix initially structured as objects by variables. As a result, both methods enable extracting the maximum contribution of the data since they can deal with categorical and numeric variables, typically the case for traffic crash data. In terms of partitional methods, K-medoids is the common choice from the clustering algorithms with this advantage.

Hence, considering the purpose of this study, K-medoids was chosen not only for the mentioned aspects but mainly for providing a cluster center, a medoid, which is an actual object of the cluster for which the average dissimilarity to all the other objects of the cluster is minimal (Kaufman and Rousseeuw, 1990a). Therefore, the medoid can be interpreted as the best representative of the cases grouped in that cluster.

In this study, we choose the PAM algorithm from the R package ‘cluster’ that operates in two phases, BUILD and SWAP. In the BUILD phase, an initial clustering is obtained by the successive selection of representative objects until k (the predefined number of clusters) objects have been found, whereas the SWAP phase attempts to improve the set of representative objects (Kaufman and Rousseeuw, 1990b). Both phases rely on the dissimilarity between objects.

Although dissimilarities can be obtained in several ways, since our database comprises categorical and numeric variables, the Gower distance measure was chosen. More specifically, we used the function DAISY in the R package ‘cluster’. In this function, the dissimilarity between two rows (d_{ij}) is the weighted mean of the contributions of each variable (Maechler et al., 2019) (see **Equation 1**).

$$d_{ij} = d(i, j) = \frac{\sum_{k=1}^p w_k \delta_{ij}^{(k)} d_{ij}^{(k)}}{\sum_{k=1}^p w_k \delta_{ij}^{(k)}} \quad (2)$$

Where p is the total number of variables (or columns in the dataset), and w_k is the weights assigned to specific variables that are more important than others (Gower, 1971). δ_{ij} is zero or one, zero when the variable is missing in either or both rows, or when the variable is asymmetric binary, and both values are zero. In all other situations, it is one. If the variable is symmetric, the simple matching coefficient is used. Otherwise, the Jaccard coefficient is computed. Finally, d_{ij} is the k -th variable contribution to the total distance.

For nominal or binary variables, the contribution d_{ij} to the total dissimilarity is zero if both values are equal and one otherwise. The contribution of numerical variables is the absolute difference between both values, divided by the total range of that variable. In the case of ordinal variables, their scores are first replaced by their rank number (r_{if}) of the i -th object in the f -th variable with ordered categories ($1, 2, \dots, M_f$), and after the absolute difference between the new scores (Z_{if}) is calculated, as in **Equation 2**.

$$Z_{if} = \frac{r_{if} - 1}{M_f - 1} \quad (3)$$

All the individual contributions d_{ij} are in between [0, 1]. Thus, the total dissimilarity will remain in this range. This study did not input weight to any variables, nor have any missing values or even asymmetric binary variables. Variables were treated as nominal or numeric, as the next section will clarify in detail.

4.4. DATA

This paper used the Road Federal Police (PRF) crash database combined with data from the federal highway inventory of the National Department of Transport Infrastructure (DNIT) of three Brazilian rural highways in the Rio Grande do Sul state. This process was done to provide detailed information about the highways' horizontal and vertical geometry, which is not usually available in police reports. The three segments account for approximately 500 km, and the crash data refers to three years, from 2017 to 2019.

Furthermore, we were interested in studying drivers' behavior in risky scenarios where road geometry had potentially played a significant role. Therefore, after an in-depth analysis of each police report, only 488 single-vehicle crashes involving loss-of-control in rural settings remained in the database since vehicles in this type of environment are typically under free-flow conditions, and drivers' choice of speed and trajectory reflects better their response to road geometric characteristics than in an urban environment (Török, 2011).

All the variables admitted to the clustering analysis were intended to contribute to the scenario simulation design effectively. Thus, from the vertical and horizontal alignment, three variables describing the segment (m_ccrv , m_hill , and m_ccr) and two variables describing the crash location ($comb_v$ and $comb_h$) were included. **Table 4.1** shows in detail each variable, its categories, and how they were considered in the CA (nominal or numeric).

The first three variables (m_ccrv , m_hill , and m_ccr) resulted from the application of R package 'segmented' to adjust a regression model with a piecewise linear relationship and multiple break-points between the cumulative segment length and: (i) the cumulative curvature change rate of the vertical alignment considering only the curves with a change in grade sign (m_ccrv), (ii) the cumulative elevation (m_hill), and (iii) the cumulative curvature change rate of the horizontal alignment (m_ccr). They were intended to describe the overall road geometry environment in which the driver is embedded, characterizing the frequency of curves (vertical and horizontal) and if the driver is climbing or descending a hill.

The other two variables ($comb_v$ and $comb_h$) combine the categories of ramps and vertical curves and tangents and curves, respectively. It is important to note that the curve classification considers the radius of the curve and its central angle, as shown in **Table 4.2**. This arrangement is based on the Brazilian Manual of Traffic Signs (CONTRAN, 2007) to warn for turns and sharp turns. Similarly, the ramp classification considers the grade standards for the flat and mountainous terrain regarding the roads' class in this study (DNER, 1999).

Next, the vertical variables (m_hill and $comb_v$) considered the active driver's driving direction (northbound/southbound). The indication of an 'active driver' here means that some crashes ended up involving more than one vehicle, but the 'active driver' was the one that lost his/her control, usually going through the opposite traffic lane, and crashing into another vehicle.

Table 4.1: Cluster variables

	Variable	Type	Min-Max	Description
Vertical	m_ccrv	numeric	0.016 to 0.52	The inclination of the adjusted line between the cumulative vertical curvature change rate and the cumulative segment length
	m_hill	numeric	-57 to 57	The inclination of the adjusted line between the cumulative elevation and the cumulative segment length considering the active driver direction
	comb_v	nominal	-	Five categories of ramp inclination (< -6%; -6% -3%; -3% -3%; 3% -6%; ≥6%) and Four types of curves (types 1 to 4 as in (American Association of State Highway and Transportation Officials - AASTHO, 2018))
Horizontal	m_ccr	numeric	0.03 to 7.45	The inclination of the adjusted line between the cumulative horizontal curvature change rate and the cumulative segment length
	comb_h ^a	nominal	-	Six types of tangents (0 -250; 250 -500; 500 -750; 750 -1000; 1000 -1250; ≥1250m) and Five types of curves (see Table 4.2)
Cross-section	lane	binary	-	Single or two lanes (in the active driver direction)
	shoulder	binary	-	With or without (considering the active driver direction)
Traffic	vph	numeric	13 to 1 627	The estimated traffic flow (vehicles per hour) considering the location, day of the week, and hour of the crash
Environment	visibility	nominal	-	Four levels resulting from the junction of variables “weather condition” and “time of the day”: clear day; clear night; dim day; dim night

^a Considering curves with $R \geq 1000\text{m}$ and $\alpha < 20^\circ$ or $R \geq 800\text{m}$ and $\alpha \leq 10^\circ$ classified as Tangents

Table 4.2: Curve classification

Category	Radius (m)	Central angle
1	$R \leq 60$	$\alpha > 30^\circ$
2	$60 < R \leq 120$	$\alpha \geq 45^\circ$
3	$60 \leq R < 120$	$30^\circ \leq \alpha < 45^\circ$
4	$120 \leq R < 450$	$\alpha > 45^\circ$
5	others	others

Lane and shoulder also consider the direction of the active driver and express whether in the driver traffic flow direction, the road geometry was a two-lane or single lane (typically, two-lanes are related to climbing lanes in this case) and in the case of the shoulders, whether there was or there was not a significant shoulder in the driver’s side. The shoulder classification was subjective, based on a visual analysis of every segment (curve/tangent) since the inventory did not have this data at such a disaggregated level. **Figure 4.2** shows an example of a significant (categorized as one) and not significant shoulder (considered as zero).



Figure 4.2: Example of the road with shoulder and without shoulders

Furthermore, to guide the choice of the traffic flow during the crash in the simulated scenario, the volume of vehicles per hour was estimated based on the traffic counting and modeling of the National Traffic Counting Plan (DNIT, 2020), considering the hour, the location, and the day of the week of the crash. This number is the traffic volume of both directions, typically evenly divided considering the highways in this study. Finally, the visibility variable originated from the junction of the weather condition and the period of the day when the crash occurred.

4.5. RESULTS

The clustering analysis resulted in four clusters (see **Table 4.3**). The choice of four clusters considered the objective of having a catalog of scenarios representative of the whole sample but without having clusters that would summarize only a few crashes. Therefore, it was settled a minimum of at least 30 crashes per cluster. With this limit and the analysis of the average silhouette width (see **Figure 4.3**), a balance between homogeneity within the clusters and diversity of scenarios was reached with the four-scenarios arrangement.

Moreover, with four groups, all the variables had an evident contribution to the distinction between scenarios. For instance, considering three groups, all the scenarios would have represented cross-sections with just one lane. It was only with four clusters that the diversity in this characteristic appeared in one scenario. A similar situation occurred with the driver's age and sex, which were initially considered for the CA to create an association between a group of interest and a particular scenario. However, since most drivers were male and their age distribution also concentrates around 40 years old, these characteristics would be the same for all clusters. Therefore, those features were not included in the CA. This subject is further explained at the end of this section.

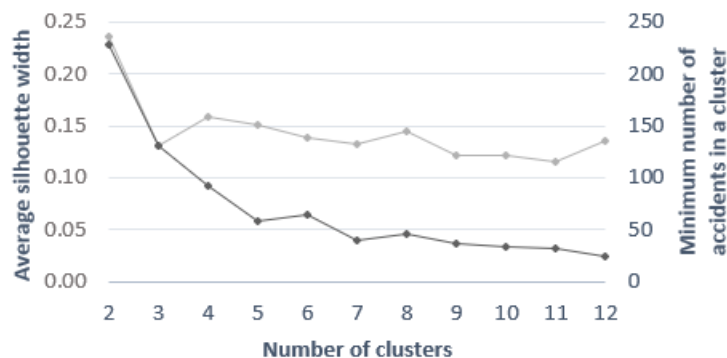


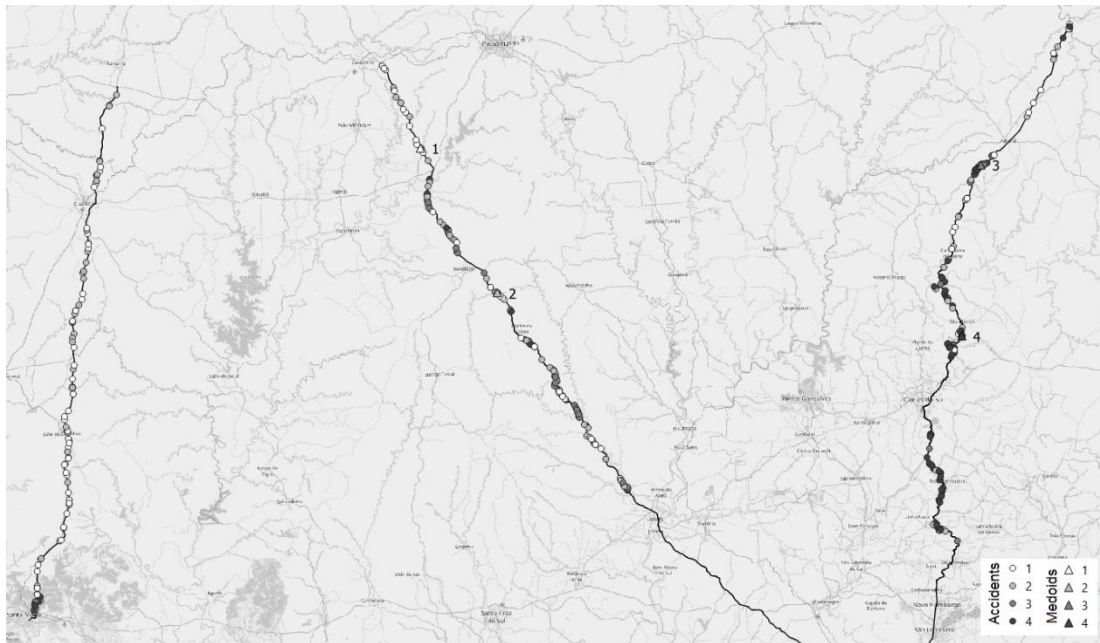
Figure 4.3: Average silhouette width (grey) and the minimum number of crashes (black) per cluster

Table 4.3: Scenarios

	Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster size	-	147	92	127	122
Vertical	m_ccrv	0.02	0.02	0.12	0.08
	m_hill	-1.98	-1.63	6.91	0.72
	comb_v	ramp -3% - 3%	sag type 3	crest type 2	crest type 2
Horizontal	m_ccr	0.08	0.08	0.77	1.42
	comb_h	straight ≥ 1250 m	curve $R \geq 450$ m	curve $\alpha > 45$ $R 120$ - 450m	straight < 250 m
Cross-section	lane	one	one	two	one
	shoulder	yes	yes	no	no
Traffic	vph	245	102	237	99
Environment	visibility	clear day	clear night	clear day	clear day

An analysis of **Figure 4.4**, which is the spatial crash distribution by clusters in the three rural highways, shows that Cluster 1 appears mainly on the far-left road (BR-158), in the middle road (BR-386), and at the beginning of the far-right road (BR-116). Cluster 2 is the most well-distributed throughout the road network. Cluster 3 is the smallest cluster of all and can be seen predominantly in the middle road but in some specific segments in the far-right and far-left roads. Cluster 4 is mainly associated with the far-right road, the final part of the far-left road, and has some crashes sparsely distributed in the middle road.

Furthermore, it can be noted that Cluster 1 and 2 are strongly blended spatially. Together, they account for 60% of the sample crashes. The shoulder's presence characterizes this first group, while in the second group (Cluster 3 and 4), there is no shoulder where the crash happened. Overall, this feature is related to space restrictions and higher costs when the roads were constructed. Hence, the choice of only two clusters would likely divide the crashes that happened in flat terrain (Clusters 1 and 2) and crashes that happened in mountainous terrain (Clusters 3 and 4); however, this macro segmentation would not have revealed interesting distinctions between the scenarios, which will be discussed in the next section.

**Figure 4.4:** Crash spatial distribution by cluster

4.6. DISCUSSION

Even though the medoids of Clusters 1 and 2 are not near located, they share many characteristics. The cross-section for both scenarios is the same, composed of one lane and shoulder in the active driver's direction. Both have the same overall environment with few vertical and horizontal curves and are associated with a similar descending alignment. However, in Cluster 1, crashes are associated with a long straight segment combined with a gentle ramp, while in Cluster 2, crashes occurred in a sag vertical curve type 3 and large curves. The two clusters also differ from each other on visibility and traffic volume variables. Crashes in Cluster 1 occurred during a clear day with higher traffic volume; meanwhile, in Cluster 2, they occurred during the night, with good weather conditions and less traffic.

These results suggest that both clusters might be the outcome of speeding since many of those elements usually do not impose a speed restriction on drivers. Regarding the geometry, operating speed models support this conclusion since they are usually oriented toward horizontal alignment restrictions marked by horizontal curves (Castro et al., 2012), and in the case of Cluster 2, large curves would not impose such restrictions. Therefore, on tangents or large horizontal curves, the operating speed is assumed to be the drivers' desired speed (Castro et al., 2012; Fitzpatrick et al., 2000). Furthermore, even with Cluster 1 having more than twice the traffic registered in Cluster 2, it is still a considerably low traffic flow for the road's characteristics. For example, considering the highest value of 245 vehicles per hour in both directions pointed out by the CA, it would produce an average headway of 30 seconds between vehicles in the same traffic lane. Although headway varies significantly under such low traffic volume, drivers would likely choose their preferable speed.

Moreover, we can speculate that in Cluster 1, the drivers could be more aware of their risky behavior, and consciously took it since the conditions are the most favorable regarding road geometry and visibility. However, Cluster 2 might indicate the drivers' misjudgment of the necessary vehicle control needed to cope with the lower visibility and tiredness during the night period and the sag curve. Thus, we can hypothesize that the first cluster could result from violations, and the second is the consequence of a mistake. According to Reason (2008), violations would require an explanation of social and motivational factors, whereas the individual's information-processing characteristics may explain mistakes in the second cluster.

Next, the remaining clusters typify crashes in mountainous environments. Cluster 3 is the only one that shows crashes in two-lane cross-sections. It is common for roads in this region to have made a trade-off between the addition of a climbing lane and the absence of shoulders, but this is only possible where the space restrictions are not excessively severe. Therefore, the bendiness in this cluster is lower than in Cluster 4. However, since it is associated with climbing lanes, it has the steepest ascending alignment and several vertical curves.

Furthermore, this cluster depicts crashes in a crest curve type 2 combined with a horizontal curve (with a central angle higher than 45° and a radius between 120m and 450m). The scenario is completed with low traffic flow and good lighting and weather conditions. A possible interpretation of this scenario is that even with a large cross-section (two lanes, although no shoulder), in an upward grade, with favorable visibility conditions, the horizontal curve with a large central angle and medium radius could be a challenge in terms of vehicle control.

As already mentioned, horizontal curves are the most influential factor in drivers' speed choices. Concerning driving simulator experiments, several studies agreed that in small radius drivers had recognized the risk and adjusted their speed, slowing down; however, on the other hand, they also indicate that the effects on the dispersion of trajectory were higher as the radius got smaller (Bella, 2013; Ben-Bassat and Shinar, 2011; Y. Chen et al., 2018; Jeong and Liu, 2019; Liu et al., 2016;

Xie et al., 2019). Nevertheless, the relationship between the radius and the lateral position measures was not as straightforward as speed, suggesting that other factors significantly affected drivers' behavior.

Nevertheless, the risk of crashes seems to increase consistently as the radius decreases, although significant differences in crash modification factors (CMF) of different countries were found, especially for radii smaller than 200m (Elvik, 2013). The author's opinion to explain this divergence is the general alignment of some countries' road networks that could lead to familiarity with sharper curves by drivers. Therefore, since those differences indicate that only a small curve radius is not a sufficient condition for danger, in this study, we took special attention to including the central angle to categorize curves, which is a characteristic often disregarded in many studies.

Next, Cluster number 4 clearly illustrates space restrictions: a cross-section without a shoulder, only one lane, and many curves along the horizontal alignment. In the vertical alignment, some vertical curves and a mild ascending vertical alignment. Clear day and low traffic flow are also part of this scheme. Here, crest curve type 2 combined with a short straight segment, is where the crash happened. Crashes in this cluster are probably associated with the frequency of horizontal curves followed by small tangents. Indeed, analyzing the distribution of the categories' frequencies in this variable (comb_h), the second most frequent category is small curves of type 2, with a large central angle and small radius (see **Table 4.2**). This fact is also the case for Cluster 3.

There is still some controversy if sequences of curves would be a higher or lower risk for crashes (Elvik, 2019; Papadimitriou et al., 2019; Zia et al., 2019). Thus, this cluster is an opportunity to analyze this issue further. Especially considering that in driving simulator experiments, it is typical to isolate the effects of one geometry to another using long tangents between curves; however, distances could vary hugely (from 150m to 2200m, for example) (Bella, 2014). Undoubtedly, drivers' performance between curves depends on many parameters such as vehicle power, geometric road features, and driver motivation, but the scenario of Cluster 4 would likely be a case where drivers' performance in tangents was affected by the previous segment.

Finally, the subject of the participants' requirements must be addressed. The police records contained both the age and sex of the drivers involved in the crashes; however, only 10% of the drivers were female, and most of them were around 40 years old, consisting of a highly homogeneous sample. Henceforth, segmentation based on these features did not contribute to the Clustering Analysis. Nevertheless, those characteristics can still be used to define the target population for the experiment. Therefore, a sample of participants with age normally distributed, similar to **Figure 4.5** (age mean of approximately 40 years old, and standard deviation of 13 years), should be pursued for the experiment.

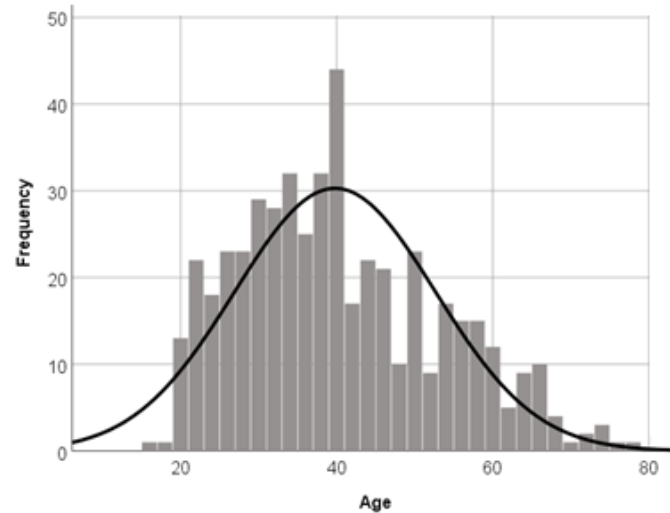


Figure 4.5: Histogram for driver age. Age mean = 39.78 years old, standard deviation = 12.86 years

4.7. CONCLUSIONS

Although several studies have often cited crash occurrences as a motivation for developing a simulated scenario and testing driver performance, decisions regarding those aspects do not often rely directly on traffic crash data analysis. In this paper, we have proposed a new framework based on Clustering Analysis (K-medoids) to support the definition of driving simulator experiments based on real crash data when the purpose is to investigate driver behavior under risky road conditions to improve road safety.

Several past studies have proven that Clustering Analysis is efficient in grouping and reducing the diversity encountered in typical crash databases; however, its general use has been mainly in data modeling and not in scenario development for simulator experiments. The studies that successfully applied this technique to develop test scenarios are mainly related to vehicle safety systems; however, using different datasets, considering their research purposes.

Therefore, we applied the proposed Clustering Analysis to the typical crash data of three Brazilian rural highways. Results showed that it was possible to compile the diversity presented in the data into four clusters that represented and summarized the crashes' main characteristics in the region of study. The clustered scenarios discovered in this paper showed a combination of factors that constructed the risky scenarios. Moreover, since the environment imposes restrictions on the road infrastructure, there are combinations of features frequently associated with each other, such as hilly roads and the absence of shoulders. Regarding the participants' requirements for the experiment, since our dataset was highly homogeneous, it did not contribute to the clustering analysis. Nevertheless, it was used to define a target population for the experiment, which in our dataset was middle-aged male drivers.

The new framework points out the benefits that driving simulator experiments could take of *a priori* analysis of traffic crashes since scenarios would be automatically selected by the CA, connected to real situations, directing the safety analysis to specific road segments. Furthermore, it can also identify a target population for the experiment, which, if it does not solve the problem of sample representativeness, at least can orient participants' recruitment.

Finally, it is expected that if there are factors systematically influencing traffic crashes, simulations based on traffic crash data will eventually show some repetitiveness throughout studies, easing the summary of findings and consolidation of results from this type of experiment.

Nevertheless, a recurrent limitation in the studies based on crash data is underreporting and lack of information since some important predictors, which may also have influenced crash occurrences, were not available in the datasets (e.g., drivers' alcohol test results from all drivers or the presence of traffic barriers along the road). Therefore, more complete data would further enhance the road conditions' ascertainment during the crash and improve driving simulator experiments.

Overall, the proposed approach's application can guide the scenarios and participants' definitions based on real crash data, leading to a clear comprehension of the crash dynamics during the driving simulator experiments, and efficiently supporting the safety analysis and possible improvements.

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5

NEW VERSION OF DRIVER BEHAVIOUR QUESTIONNAIRE TO INVESTIGATE DRIVER BEHAVIOUR ON RURAL ROADS

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Behavioral research often considers self-report data and several traffic safety studies have used questionnaires to assess driver behavior. Until now, the focus was on road crash contributing factors; therefore, the fourth paper is the first step to include the human factor. In order to do so, the Driver Behavior Questionnaire (DBQ), developed by Reason et al. (1990), was adopted.

In Reason et al.'s theory, the authors distinguish three types of failures (errors, violations, and lapses), advocating that different types of failures demand different modes of remediation and could also be associated with different types of individuals. As mentioned in the Introduction (chapter 1), Reason (2008) promoted the philosophy of error management called the *System Approach*; on that account, road safety studies interested in driver behavioral history commonly consider the DBQ in their research.

The inclusion of the DBQ into the analysis was not intended to condense all the human influence on a measure, especially when considering the multifactorial nature of crashes, but to add a piece of information to the human factor understanding. The new version was needed to tailor the questionnaire, improving the tool's assertiveness to the conditions and target subpopulation identified in the previous paper (chapter 4) for the driving simulator experiment.

ABSTRACT

The Driver Behaviour Questionnaire (DBQ) has been one of the most applied tools to evaluate driver behaviour. The questionnaire makes a clear distinction between errors and violations, where the errors subscale tends to reflect misjudgments or failures of observation, and the violations subscale reflects the deliberate contraventions of safe driving practice. Several variants of the questionnaire were created to adapt the tool to the local culture, modern habits, or research-specific aims. In this study, we adapted a 28-item version of the DBQ to select later drivers based on their scores on Errors (E), Ordinary Violations (OV), and Aggressive Violations (AV) to participate in a driving simulator experiment in rural road settings. Through Categorical Principal Component Analysis (CATPCA) and Confinaltory Analysis, the chosen three-dimension structure for the new DBQ consisted of ten Errors, five Ordinary Violations, and five Aggressive Violations. Many of the error items from the original DBQ were maintained; however, one error item switched to the OV dimension, and new items were preferred over the traditional ones in the OV dimension. Furthermore, two additional items were included in the AV dimension. The new version represents better behaviours in rural road settings and is expected to improve drivers' classification.

KEYWORDS: Driver Behaviour Questionnaire; Portuguese

5.1. INTRODUCTION

The Driver Behaviour Questionnaire (DBQ) has been one of the most applied tools to evaluate driver behaviour. In 1990, Reason et al. (1990) presented a questionnaire containing 50 items regarding typical traffic situations to 520 drivers who answered how frequently they had engaged in such behaviours during the previous year on a scale between 0 (never) to 5 (nearly all the time). The authors identified three distinct factors accounting for 33% of the total variance: violations, dangerous errors, and relatively harmless lapses. They concluded that the Principal Component Analysis (PCA) made a clear distinction between errors and violations; however, not all traffic situations were significant for this distinction. Reason et al. (1990) reported only 26 items with factor loadings above 0.50 (eleven violations, eight errors, and seven lapses).

The following studies by Parker et al. (1995) and Lawton et al. (1997) consolidated a short form of the DBQ composed respectively of 16 items (eight errors and eight lapses) and 12 items (usually considered nine ordinary violations and three aggressive violations, but initially classified into three factors: fast speeding, maintaining progress, and anger/hostility). Overall, this popular version included 28 items in total, as shown in **Table 5.1**.

The DBQ has since been replicated in several different countries, with slight differences among the versions. The questionnaire's variants were created to include culture-specific situations, other types of drivers (professional, motor riders), other groups (pedestrians, children) (de Winter and Dodou, 2010), or updated items such as cell phone use (Cordazzo et al., 2016). Despite that, Reason et al.'s work has maintained the idea of differentiating errors and violations since many items loaded consistently in the same factor.

Nevertheless, it is important to pay attention to the questions (items), as some controversy may emerge. For instance, in the meta-analysis conducted by de Winter and Dodou (2010), the items loading in the factor "stunt" in the paper of Sakashita et al. (2014) were classified as violations; however, in the meta-analysis of af Wählberg et al. (2015, p.191) they did not include this factor since the stunt items were considered "very different from the standard DBQ violation items".

Regarding the Brazilian and Portuguese versions, the literature search retrieved three papers that tested or adapted the DBQ in a Brazilian sample, two papers in a Portuguese sample, and one study that mixed both nationalities, as shown in **Table 5.2**. As can be seen, those studies revealed factor structures from three to ten dimensions. Arguably, this result was influenced by the initial DBQ version the authors choose for their study, with more or fewer items. Campos et al. (2020), Bianchi and Summala (2002), and Dourado et al. (2017) reported some discrepancies regarding the original DBQ, such as items loading on different factors or items that had loadings lower than 0.3 in all factors.

As an example, in Campos et al. (2020), the item "Pull out of an intersection so far that the driver with right of way has to stop and let you out" intended to load on the factor Ordinary Violations, loaded instead on Errors. The authors speculated that this change could be related to cultural characteristics. To Özkan et al. (2006), traffic culture likely determines formal and informal rules for acceptable driving style; thus, differences among cultures are expected.

Table 5.1: 28-DBQ popular version

Code	Class	Item
-	L	Attempt to drive away from traffic lights in third gear
-	L	Forget where you left your car in car park
-	L	Switch on one thing, such as the headlights, when you meant to switch on something else, such as the wipers
-	L	Realise that you have no clear recollection of the road along which you have just been travelling
-	L	Misread the signs and exit from a roundabout on the wrong road
-	L	Hit something reversing that you had not previously seen
-	L	Intending to drive to destination A, you "wake up" to find yourself on the road to destination B, perhaps because the latter is your more usual destination
-	L	Get into the wrong lane approaching a roundabout or a junction
DBQE01	E	Attempt to overtake someone that you had not noticed to be signalling a right turn
DBQE02	E	Fail to notice that pedestrians are crossing when turning into a side street from a main road
DBQE03	E	Brake too quickly on a slippery road, or steer the wrong way into a skid
DBQE04	E	Miss 'Give Way' signs, and narrowly avoid colliding with traffic having the right of way
DBQE05	E	Fail to check your rearview mirror before pulling out, changing lanes, etc.
DBQE06	E	Queueing to turn left onto main road, you pay such close attention to the main stream of traffic that you nearly hit the car in front
DBQE07	E	On turning left, nearly hit a cyclist who has come up on your inside
DBQE08	E	Underestimate the speed of an oncoming vehicle when overtaking
DBQV09	OV	Disregard the speed limit on a motorway
DBQV10	OV	Disregard the speed limit on a residential road
DBQV11	OV	Race away from traffic lights with the intention of beating the driver next to you
DBQV12	OV	Stay in a lane that you know will be closed ahead until the last minute before forcing your way into the other lane
DBQV14	OV	Pull out of a junction so far that the driver with right of way has to stop and let you out
DBQV13	OV	Overtake a slow driver on the inside
DBQV15	OV	Cross a junction knowing that the traffic lights have already turned against you
DBQV16	OV	Drive so close to the car in front that it would be difficult to stop in an emergency
DBQV17	OV	Drive when you suspect you might be over the legal blood alcohol limit
DBQV18	AV	Become angered by a certain type of driver and indicate your hostility by whatever means you can
DBQV19	AV	Sound your horn to indicate your annoyance to another driver
DBQV20	AV	Become angered by another driver and give chase with the intention of giving him/her a piece of your mind

Note: AV = Aggressive Violations, OV = Ordinary Violation, E = Errors, and L = Lapses.

Table 5.2: DBQ studies

Author, date	Country	Final structure
Bianchi and Summala, 2002	BR	4 Factors: 5 Lapses, 10 Errors, 7 Ordinary Violations, and 4 Aggressive Violations
Brites et al., 2006 apud Bação, 2015	PT	5 Factors: 6 Lapses, 6 Inattention Errors, 6 Non-intentional Violations, 6 Violations, and 4 Sensation Seeking
Pinatti, 2007	BR	10 Factors: 8 Deliberate Violations, 6 Non-intentional Violations, 5 Dangerous Errors, 3 Inexperience, 5 Ordinary Violations, 2 Distractions, 3 Inattention, 3 Mistakes, 2 Errors, and 2 Lapses
Veiga et al., 2009	BR	3 Factors: 13 Lapses, 13 Errors, and 13 Violations
Dourado et al., 2017	PT	3 Factors: 6 Lapses, 9 Non-intentional Errors, and 7 Impulsive and Aggressive driving
Campos et al., 2020	BR/PT	3 Factors: 9 Errors, 8 Ordinary Violations, and 3 Aggressive Violations

Despite some controversy regarding the behavioural validity of the DBQ (af Wählberg et al., 2015), some authors classified drivers using a validated version of the DBQ and found differences in their objective driving measures. Helman and Reed (2015) revealed that the DBQ violations subscale was associated with speed, while the error and lapse sub-scales were not, although the authors had called attention to the small sample size used in their study. Similarly, Zhao et al. (2012) showed that drivers with high violation scores were likely to drive faster, have poorer lateral control, change lanes more frequently, spend more time in the left lane, and have more sudden unidirectional accelerations. The authors did not observe any main effects between error scores and any of the driving behaviour measures. They evaluated 108 drivers; however, participants who self-reported being involved in a police-reported crash within the past year were excluded from participation as a safety precaution since it was an on-road study.

Therefore, this study aims to adapt the DBQ to the local culture and modern habits, as well as to meet the needs of the research. The new version will be used to classify and select participants through the DBQ items based on drivers' scores in violation and errors for a driving simulator experiment considering rural road risky scenarios in the context of an ongoing Ph.D. thesis at the University of Porto. Thus, the correct interpretation and adequacy of the DBQ to the sample are crucial.

Hence, in this study, the objective is to compare the fit of a new DBQ version derived from the traditional items of the DBQ plus 12 additional items focused on rural road situations against the original DBQ version. Since the intended sample for the simulator experiment is Brazilians living in Portugal, a merged database composed of Brazilians and Portuguese is used in this study. A future study is expected to investigate differences in those populations.

5.2. MATERIALS AND METHODS

5.2.1. DRIVER BEHAVIOUR QUESTIONNAIRE

The online questionnaire was divided into three parts. The first one asked about demography: age, sex, nationality, the country where you live, driver's licence ownership, weekly frequency of driving, professional driver status, and involvement in active crashes as a driver (where the driver recognises that at least part of the crash cause was due to his/her behaviour) in the past three years. The second part listed 20 questions (errors and violations) from **Table 5.1**. This choice was made because both errors and violations are potentially dangerous to crash occurrences, while lapses are unlikely to impact driving safety (Reason et al., 1990). Moreover, one item from the OV's in **Table 5.1** was replaced by a similar situation, only emphasising the violation aspect ("Overtake a slow driver on the inside" replaced by "Become impatient with a slow driver you are driving behind and overtake in a risky way").

The third part had 12 new items based on other papers, as **Table 5.3** shows. Since this questionnaire is part of another research that aims to study driver behaviour on rural roads, the addition of those items was intended to adapt and improve the performance of the DBQ regarding those circumstances. All the traditional and new items were slightly modified after the translation process and the results of the pilot studies (see **Supplementary Material**).

Table 5.3: Extra items

Code	Class	Source	Item
EXTE01	E	Maslać et al., 2018	I miscalculated the duration of the green light on the traffic lights, and I could not stop the vehicle safely
EXTE02	E	Martinussen et al., 2013	Turning right on to a main road into the path of an oncoming vehicle that you had not seen or whose speed you had misjudged
EXTE03	E	Cordazzo et al., 2016	Have to break in the middle of a curve or on a ramp because you are driving too quickly
EXTV04	V	Maslać et al., 2018	I intentionally drive slowly in order to annoy the drivers behind me
EXTV05	V	Reason et al., 1990	Drive especially close or 'flash' the car in front as a signal for that driver to go faster or get out of your way
EXTV06	V	Krahé and Fenske, 2002	Accelerate while the other driver is overtaking you
EXTV07	V	Veiga et al., 2009	Overtake when there is a continuous line indicating that it is prohibited
EXTV08	V	Veiga et al., 2009	Make a U-turn crossing a continuous line where it is not allowed to return
EXTV09	V	Shao et al., 2020	Continuous lane change or rapid acceleration/deceleration
EXTV10	V	Alketbi et al., 2020	Drive without a valid license because it had been suspended
EXTV11	V	Campos, 2019	Use your phone with your hands while driving
EXTV12	V	Cordazzo et al., 2016	Get told by a passenger to calm down because you are angry at other drivers

Note: V = Violations, E = Errors.

5.2.2. PARTICIPANTS

A total of 1,321 respondents completed the questionnaire, 652 Brazilians living in Brazil, and 669 Portuguese living in Portugal. The participation was voluntary, and their anonymity was ensured. The survey was disseminated through personal and institutional e-mail messages and other social media such as Facebook. Respondents who did not hold a driver's license were excluded. Regarding the total sample, 51.6% were female, the mean age was 32 years old (age range 18-82 yo), and 11% work or worked as a professional driver. The percentage of weekly driving was high, with 44.6% reporting to have driven six or more times a week, 19.8% five or four times, 19.2% two or three times, and 16.4% one or less. Most drivers (82.66%) were not involved in an active car crash in the last three years.

5.2.3. EXPLORATORY DATA REDUCTION TECHNIQUES

Nonlinear Principal Component Analysis (NLPCA) was performed to explore relationships between the variables and reduce the information from the dataset (DBQ original + extra items). Although Factor Analysis (FA) and Principal Component Analysis (PCA) are the most common statistical techniques used to derive DBQ factors (de Winter et al., 2015), the NLPCA has the advantage of dealing not only with quantitative data but with mixed measurement levels and nonlinear relationships (Linting and Van Der Kooij, 2012). These characteristics are particularly useful for ordinal data such as the Likert Scale (Linting and Van Der Kooij, 2012).

In a recent study, Campos et al. (2020) examined three techniques for DBQ validation: Factor Analysis, Principal Component Analysis, and Nonlinear Principal Component Analysis, with the latter being more advantageous than the others regarding the representation of the original data

and the data constraints. Furthermore, in their study, NLPCA explained 11% more variance than FA and 2% more than PCA. In this study, the NLPCA in the statistical software package SPSS 27, named Categorical Principal Component Analysis (CATPCA) (IBM Corp., 2020), was used following the procedures described in Campos et al. (2020), including Varimax rotation with Kaiser normalisation.

Moreover, Confirmatory Factor Analyses (CFA) with maximum likelihood estimation was performed to examine the models fit established in the CATPCA for comparison purposes among DBQ versions. The fit of the models was compared by χ^2 /degree of freedom ratio, root mean square error of approximation (RMSEA), comparative fit index (CFI), and standardised root mean square residual (SRMR). A good fit model should have 2:1 or 5:1 χ^2 /degree of freedom ratio, CFI > 0.90 (preferably > 0.95), and RMSEA < 0.08 or 0.10 (preferably < 0.05), and SRMR < 0.08 (preferably < 0.05) indexes (Hu and Bentler, 1999; Wheaton et al., 1977). The AMOS software package (IBM Corp., 2020) was used to perform the CFA.

5.3. RESULTS AND DISCUSSION

Firstly, to examine the internal consistency and reliability of the scales, Cronbach's alpha was calculated for the original 20-items DBQ and the original + extra items (total of 32 items). Both versions indicated good results (0.83 and 0.88, respectively), and there was no improvement in the scale with the exclusion of any item. Furthermore, the Kaiser–Meyer–Olkin (KMO) measure confirmed the sample adequacy to perform the Confirmatory Factorial Analysis (0.92 and 0.88, respectively), and Bartlett's test indicated that there were correlations between variables in both datasets ($p = 0.000$). Unfortunately, these measures are not available for CATPCA.

Since the research aimed to use the DBQ to classify drivers for a future driving simulator experiment having a high or low score in each factor, only the dimensions solutions with few components were considered to simplify the possible drivers' profiles; therefore, only the two, three and four dimensions were tested. Afterwards, an iterative process of eliminating items with extremely low loadings or high loads in two or more dimensions was performed. The item was removed, a new analysis was performed, and another item was removed successively until reaching an interpretable structure (Campos et al., 2020; Hair et al., 2014). This process had the purpose of determining distinct behaviours and avoiding misinterpretation of the items. Preference was given to keeping low to medium-loading items over cross-loading items to identify different behaviours correctly.

Potential DBQ versions attending the above criteria were found in the 2-dimension 21-item version (2D-21) and 3-dimension 24-item version (3D-24). The 4-dimension solution was disregarded because the 4th dimension was associated mainly with only one item (EXTV10). The iterative process went on considering the 2D and 3D versions, removing low-loading items with higher cross-loadings until reaching a 20-item version (2D-20 and 3D-20), approximating the solutions to the original DBQ version in terms of items.

Overall, the goodness-of-fit indices show that the new 2D-21 and 3D-20 structures had a better fit than the other structures (see **Table 5.4**). None of them achieved the threshold of CFI > 0.90, but the 3D-20 version is slightly better than the 2D-21 version. Moreover, the variance explained by the 3D-20 version is the highest among all the alternatives, with Cronbach's alpha values that were considered acceptable by the authors, taking into account that there is no definitive threshold for this measure and interpretability of the instrument is critical (Cronbach, 1951; Schmitt, 1996; Taber, 2018). The percentage of variance explained and Cronbach's alpha for the original versions are not presented in **Table 5.4**. They refer to the EFA results, which were not performed for the

original versions; therefore, the data were only tested if they fit the original versions hypothesised model using CFA.

Table 5.4: CFA models' indices and EFA results

	Original 3D-20	Original 2D-20	New 2D-21	New 2D-20	New 3D-24	New 3D-20
χ^2/dof	4.978	6.605	4.046	6.155	5.718	3.980
RMSEA	0.055	0.065	0.048	0.062	0.06	0.048
CFI	0.878	0.826	0.881	0.804	0.815	0.894
SRMR	0.0451	0.0516	0.0432	0.0438	0.0776	0.0437
%Variance Explained	-	-	32.907	33.399	37.813	39.270
Cronbach's alpha	-	-	(0.80/0.77)^a	(0.80/0.75)^a	(0.81/0.81/0.70)^b	(0.77/0.73/0.67)^b

Note: ^a (Errors/Violations); ^b (Errors/Ordinary Violations/Aggressive Violations)

In fact, the superiority of the 3D-20 structure is mainly concerning the factors' interpretation, focusing on the distinction among behaviours, and therefore this version was preferred over the others. The 3D-20 version is composed of ten Errors (DBQE01-05; DBQE07; DBQE08; DBQV14; EXTE01; EXTE02), five Ordinary Violations (DBQV09; DBQV10; EXTV07-09), and five Aggressive Violations (DBQV18-20; EXTV04; EXTV12) (see **Table 5.5**). There is a clear distinction between errors, ordinary rule violations, and aggressive violations showing hostility towards other road users in this version.

An analysis of the new version structure shows that most original Error items were kept; however, an originally Ordinary Violation item switched to the Error dimension (DBQV14). This adjustment was also observed in Campos et al. (2020) and Bianchi and Summala (2002). The results considering only the Portuguese population in this study also pointed out this change.

In addition, the majority of the Ordinary Violation items were new items, and in the Aggressive Violation dimension, two new items were included. From the 12 suggested items, seven were included in the new DBQ version. They add important typical rural road errors and violations that are linked to crashes, such as "When turning right to a main street, enter in the path of an approaching vehicle that you did not see or whose speed you miscalculated" (EXTE02) or "Overtake when there is a continuous horizontal line indicating that it is prohibited" (ETXV07). Moreover, the new version included the modern and risky habit of using a cell phone while driving (EXTV11).

Considering the Aggressive Violation dimension, the additional questions EXTV04 and EXTV12 are important for characterising the AV dimension as it exceeds the threshold of at least three items for each dimension that is commonly advocated (Gorsuch, 2014; Russell, 2002). Therefore, with two more items in this dimension, this behaviour is expected to be better identified, improving drivers' classification.

Table 5.5: CATPCA dimension loadings values of the items from the 3D-20 version

Item	Dimensions		
	1 Errors	2 Ordinary Vio	3 Aggressive Vio
DBQE01	0.50	0.07	0.05
DBQE02	0.59	0.06	0.09
DBQE03	0.46	0.04	0.02
DBQE04	0.58	0.18	0.07
DBQE05	0.44	0.20	-0.09
DBQE07	0.59	-0.01	0.20
DBQE08	0.55	0.18	0.14
DBQV09	0.03	0.79	0.16
DBQV10	0.14	0.78	0.08
DBQV14	0.51	0.17	0.16
DBQV18	0.07	0.19	0.75
DBQV19	0.07	0.23	0.67
DBQV20	0.11	-0.06	0.56
EXTE01	0.57	0.14	0.05
EXTE02	0.69	0.11	0.03
EXTV04	0.05	0.08	0.44
EXTV07	0.18	0.60	0.07
EXTV08	0.20	0.55	0.10
EXTV11	0.22	0.54	0.19
EXTV12	0.08	0.12	0.66
%Variance Explained	16.186	12.382	10.702
Cronbach's alpha	0.77	0.73	0.67

5.4. FINAL CONSIDERATIONS

The Driver Behaviour Questionnaire (DBQ) has been one of the most applied tools to evaluate driver behaviour. Reason et al. (1990) identified a clear distinction between errors and violations in their famous paper. The authors stated that while errors may be defined in relation to the individual's cognitive processes, violations can be described with regard to a social context. Therefore, the errors subscale tends to reflect misjudgments or failures of observation, and the violations subscale reflects the deliberate contraventions of safe driving practice.

Even though af Wåhlberg et al. (2015, p. 203) claimed that a "thorough conceptual analysis, review, and meta-analysis would be needed for this evidence concerning behavioral validity" of the DBQ, some authors classified drivers using a validated version of the DBQ and found differences in their objective driving measures. In fact, more evidence is needed on whether the DBQ is a valid measure of observed behaviour in objective driving. Therefore, as the first step in this study, a new version of the DBQ was proposed and adapted to the local culture and modern habits to classify drivers based on their scores. The new version has three dimensions and 20 items (ten Errors, five Ordinary Violations, and Aggressive Violations). Most of the original error items were kept; however, an original ordinary violation item was included in the Error factor. In addition, the majority of the ordinary violation items were new items, and in the Aggressive Violation dimension, two new items were included, which is expected to improve drivers' classification.

The Categorical Principal Component Analysis results showed that items loaded high in a single dimension (all cross-loadings < 0.23). Moreover, each dimension presented a good internal consistency (Cronbach's alpha > 0.67), and the new version had the highest variance explained. Confirmatory Factor Analysis also favoured the new version. Therefore, the new version presented a factor structure, reliability, and internal consistency indices compatible with the traditional version of the DBQ, comprising, through the inclusion of new items, rural road situations in a satisfactory way for the study's continuity.

Nevertheless, some limitations of this study need to be addressed. First, this study used self-report measures to assess driving behaviour, which can be subjected to memory biases and participant response biases. Regardless of this issue, to reduce possible bias, drivers were assured anonymity in their responses. A second limitation relates to the sample's representativeness. Since an e-survey was used, it consists of a non-probabilistic sample, which means that the results cannot be expanded to the population. A large enough sample would overcome this problem, but associations found in subpopulations may be of interest in itself.

SUPPLEMENTARY MATERIAL

Questionnaire (PT-BR)

Considerando o período de um ano, com que frequência cada situação abaixo acontece enquanto você dirige?

1. Tentar ultrapassar um veículo que você não viu estar sinalizando para entrar à esquerda
2. Ao entrar em uma rua lateral, vindo de uma rua principal, não perceber que pedestres estão atravessando
3. Frear bruscamente em uma estrada escorregadia, ou girar o volante para o lado errado em uma derrapagem
4. Não prestar atenção aos sinais de "Dê a preferência" e evitar, por pouco, colidir com outro veículo que tem a preferência de passagem
5. Não verificar seu espelho retrovisor antes de arrancar, mudar de faixa, etc.
6. Estar em uma fila para entrar em uma rua principal e prestar tanta atenção no trânsito dessa rua, que quase bate na traseira do carro à sua frente
7. Ao virar uma esquina, quase bater em um ciclista que apareceu do seu lado
8. Subestimar a velocidade de um veículo que está vindo no sentido contrário ao iniciar uma ultrapassagem
9. Desrespeitar o limite de velocidade em uma rodovia
10. Desrespeitar o limite de velocidade em uma rua residencial
11. Arrancar nos semáforos com a intenção de ser mais rápido que o motorista ao seu lado
12. Ficar em uma faixa que você sabe que estará interrompida adiante e forçar sua entrada na outra faixa, no último instante
13. Quando você está dirigindo atrás de um veículo que anda lentamente, impientemente você ultrapassa de maneira arriscada
14. Parar em um cruzamento tão para a frente que o motorista que tem preferência precisa parar e deixar você passar
15. Atravessar o cruzamento sabendo que o semáforo já fechou para você
16. Dirigir tão próximo ao veículo da frente que seria difícil parar em uma emergência
17. Dirigir após consumir bebida alcoólica
18. Ficar muito bravo com um determinado tipo de motorista e indicar sua hostilidade de qualquer maneira
19. Buzinar para indicar sua contrariedade com relação a outro usuário da via
20. Ficar muito bravo por causa de outro motorista e persegui-lo com a intenção de dizer o que você pensa dele
21. Calcular mal a duração do sinal verde nos semáforos e ter que frear abruptamente para conseguir parar o veículo
22. Ao virar à direita para ingressar em uma rua principal, entrar no caminho de um veículo que se aproximava, mas que você não viu ou cuja velocidade você calculou mal
23. Ter que frear no meio de uma curva porque você estava dirigindo muito rápido
24. Dirigir intencionalmente devagar para incomodar o motorista atrás de você
25. Dirigir muito perto do carro à sua frente como sinal de que ele deve dirigir mais rápido ou sair da faixa
26. Acelerar enquanto um motorista o ultrapassa
27. Ultrapassar quando existe sinalização horizontal de linha contínua, indicando que é proibido
28. Fazer um virada em "U" cruzando uma sinalização horizontal de linha contínua, onde é proibido retornar
29. Ficar mudando de faixa de forma contínua
30. Dirigir com a carteira de motorista suspensa ou cassada
31. Usar o celular com as mãos enquanto dirige
32. Um passageiro disse para você se acalmar devido ao seu comportamento em relação aos outros motoristas

Questionnaire (PT-PT)

Considerando o período de um ano, com que frequência cada situação abaixo acontece enquanto conduz?

1. Tentar ultrapassar um veículo que você não viu que estava a sinalizar uma viragem à esquerda
2. Ao virar para entrar numa rua lateral, vindo de uma rua principal, não perceber que existem peões a atravessar
3. Travar bruscamente numa estrada escorregadia, ou rodar o volante para o lado errado numa derrapagem
4. Distrair-se e não reparar no sinal de STOP ou de perda de prioridade e quase colidir com os veículos que têm prioridade
5. Não verificar o espelho retrovisor antes de arrancar, mudar de via, etc.
6. Estar numa fila para entrar numa rua principal, e prestar tanta atenção ao fluxo de trânsito desta rua que quase bate na traseira do carro da frente
7. Ao fazer uma curva, quase colidir com um ciclista que apareceu do seu lado
8. Subestimar a velocidade de um veículo que vem em sentido contrário, quando está a fazer uma ultrapassagem
9. Desrespeitar o limite de velocidade numa autoestrada/estrada nacional
10. Desrespeitar o limite de velocidade numa rua residencial
11. Arrancar nos semáforos com a intenção de ser mais rápido que o condutor ao seu lado
12. Ficar numa via que sabe que estará interrompida mais à frente, e forçar sua entrada noutra via no último instante
13. Quando está a conduzir atrás de um veículo que anda lentamente, impientemente você ultrapassa de maneira arriscada
14. Parar num cruzamento tão chegado à frente que o condutor com direito de passagem tem que parar para o deixar passar
15. Atravessar um cruzamento mesmo sabendo que o semáforo já ficou vermelho para si
16. Conduzir tão próximo do veículo da frente que seria difícil parar numa emergência
17. Conduzir mesmo sabendo que provavelmente ultrapassou o limite permitido de álcool no sangue
18. Irritar-se com um determinado tipo de condutor e indicar a sua hostilidade de qualquer maneira
19. Buzinar para indicar a sua discordância a outro utilizador da via
20. Zangar-se com outro condutor e persegui-lo com a intenção de dizer o que pensa dele
21. Calcular mal a duração do sinal verde nos semáforos e ter que efetuar uma travagem de emergência para conseguir imobilizar o veículo
22. Ao virar à direita para ingressar numa rua principal, entrar no caminho de um veículo que se aproximava, mas que você não viu ou cuja velocidade calculou mal
23. Ter que travar no meio de uma curva porque estava conduzindo muito rápido
24. Conduzir intencionalmente devagar para incomodar o condutor atrás de você
25. Conduzir muito próximo da traseira do carro da frente, forçando o seu condutor a conduzir mais rápido ou a sair do caminho
26. Acelerar quando está a ser ultrapassado por um veículo
27. Ultrapassar quando existe sinalização horizontal de linha contínua, indicando que é proibido
28. Fazer um viragem em “U” cruzando uma sinalização horizontal de linha contínua, onde é proibido inverter a marcha
29. Mudar de via constantemente
30. Conduzir com a carta de condução suspensa ou cassada
31. Usar o telemóvel com as mãos enquanto conduz
32. Um passageiro disse para você se acalmar devido ao seu comportamento em relação aos outros condutores

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6

EVALUATING INDIVIDUAL HETEROGENEITY IN THE PROBABILITY OF CRASH INVOLVEMENT

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The most common use of the DBQ is to evaluate driver behavioral history and its relationship with crashes. In this fifth paper, the aim was to verify the extension of this relationship, considering the new version presented in the previous paper (chapter 5), using a more sophisticated statistical model.

Although many studies have examined the relationship between driver behavior and crash involvement, the use of random-parameters (mixed) models is very limited. The random-parameter approach allows estimated parameters to vary across observations, accounting for the expected heterogeneity when dealing with behavioral data and the multifactorial contributing factors of crashes.

Therefore, there was an interest in analyzing the DBQ score association with self-reported crashes through a random-parameters model, which accounts for the unobserved heterogeneity, to extract potential new insights from crash databases and contribute to the discussion regarding the use of the DBQ for crash prediction.

ABSTRACT

The Driver Behavior Questionnaire (DBQ) is a traditional research tool to evaluate driver behavior and crash relationships. In order to investigate the DBQ score association with self-reported crashes accounting for the heterogeneity across observations, a random-parameter logit model was applied. A total of 1,321 drivers answered a DBQ version with three dimensions (Errors, Ordinary Violations, and Aggressive Violations). The results showed that, in most observations, Aggressive Violations contributed negatively to the likelihood of self-reported crashes, while the opposite was true for Ordinary Violations. The Error score represented the intermediate condition where around half of the observations contributed negatively, and the other half, positively, resulting in a non-significant mean, despite the confirmed heterogeneity. We concluded that driver behavior, translated into DBQ scores, has a heterogeneous effect on crashes. This result may be due to unobserved factors influencing crash occurrences.

KEYWORDS: Driver Behavior Questionnaire, Crash Probability, Random Parameter Models

6.1. INTRODUCTION

The Driver Behavior Questionnaire (DBQ) has been widely applied to evaluate driver behavior and its relationship with crashes. It consists of a questionnaire containing several items regarding typical traffic situations where drivers must answer how frequently they had engaged in such behaviors during the previous year (Reason *et al.*, 1990). In its first use, Reason *et al.* identified three distinct factors: violations, dangerous errors, and relatively harmless lapses. Based on Reason's findings, Parker *et al.* investigated the hypothesis that errors and violations have a distinct effect on crash liability (Parker *et al.*, 1995). They observed that the DBQ violation factor score added significantly to explain the crash rate, although the additional contribution was not large.

Crashes have multiple factors, and measuring the human influence on them is primary, but summarizing the complexity of human behavior in scores is also challenging. Despite the extensive list of following studies that examined the association of driver behavior with crash involvement (af Wåhlberg *et al.*, 2015; Bener *et al.*, 2020; de Winter and Dodou, 2010; Sullman *et al.*, 2019), the use of random-parameter (mixed) models is still minimal. The random-parameter approach allows estimated parameters to vary across observations, accounting for the expected heterogeneity when dealing with behavioral data and the multifactorial causes of crashes.

The motivation for using random parameter models is to account for unobserved heterogeneity across individuals and to extract more information from crash databases. Therefore, this paper tests a random-parameter binary logit model as a methodological approach to gain new insights into how DBQ scores significantly influence crash probability.

6.2. BACKGROUND

As mentioned, despite the extensive research on the relationship between driver behavior and crash involvement, there are still questions regarding the validity of the DBQ. The meta-analyses in this area dealt with issues such as several diversified terminologies for the DBQ factors and differences in dependent measures (all crashes *vs.* at-fault crashes, self-reported *vs.* recorded). In addition, some claim that since crashes are rare, especially when analyzed on the subject/person level, correlations are necessarily small (de Winter *et al.*, 2015). Therefore, the uncertainty of the actual role of methodological biases on the DBQ's effects on the prediction of crashes has been extensively debated.

Indeed, research methods need to be improved, including larger samples and more reliable measurements of explanatory variables, and greater focus should be given to crashes where the driver is at fault. Another area to improve is related to the statistical methodologies adopted. Arguably, sophisticated statistics can not compensate for methodological effects; however, applying a model in line with the theory assumed and the collected data's nature can allow the extraction of more information from the databases.

Considering the statistical methodologies applied by studies in this field, zero-order correlation analysis (Pearson and Spearman correlation) has served as a basis for meta-analyses in general (Af Wåhlberg *et al.*, 2015; de Winter and Dodou, 2010; de Winter *et al.*, 2015). As an example, values of the zero-order correlations were reported between .082 (af Wåhlberg *et al.*, 2015) and .13 (de Winter *et al.*, 2015) for Violations.

Meanwhile, studies often applied count models, such as Logistic Regression or Poisson Regression, to their analysis (Al Azri *et al.*, 2017; Bener *et al.*, 2020; Rachad *et al.*, 2022; Rezapur-Shahkolai *et al.*, 2020; Rowe *et al.*, 2015; Shao *et al.*, 2020; Tronsmoen, 2010; Xie and Parker, 2002; Zhang *et al.*, 2013), acknowledging that they are an appropriate approach for

modeling crash occurrences (non-negative integers). Studies also included other variables in their analysis to control for the potential influence on the outcomes, especially exposure, but also age and sex since these are essential individual-level variables related to crash rates (Berger and Hössinger, 2019; Lourens *et al.*, 1999; Moghaddam *et al.*, 2017; Ozkan and Lajunen, 2011; Warner *et al.*, 2011).

The statistical approach adopted by this study addresses the issue of applying models assuming that parameters are fixed across observations – i.e., the effect of any explanatory variable is the same for each observation or individual – given that constraining parameters to be constant when they vary could lead to inconsistent and biased parameter estimates (Washington *et al.*, 2011). The random-parameter models (also known as mixed models) have proved their potential to provide a better understanding of the contributing factors to crashes, and they have been successfully applied in transport safety research (Anastasopoulos and Mannering, 2009; Chouhan *et al.*, 2022; Riccardi *et al.*, 2022; Romo *et al.*, 2014; Truong *et al.*, 2020; Xiao *et al.*, 2021; P. Xie *et al.*, 2022).

However, the literature review indicates that unobserved heterogeneity has not been much considered in crash analyses considering DBQ scores. Some studies considered road user-level behavioral variables in their analyses, but they are usually related to the person's condition (impaired or not impaired) or the behavior/action taken before the crash. For example, Rella Riccardi *et al.* (2022) used a random parameter approach to explore the road infrastructure, environmental, vehicle, and driver-related patterns affecting pedestrian crash propensity. The authors included variables regarding driver behavior such as speeding, tailgating, and disobeying stop sign, among others, and driver psychophysical state (defective sight, impaired, and normal), besides age and gender. Only gender produced a random variable, with the male gender being associated with a higher probability of pedestrian crashes for 86% of the observations.

Another study by Xie *et al.* (2022) examined the effects of different rule-violations on the bus drivers' risk of being at fault in crashes. The independent variables included driver's characteristics such as age, gender, complaints received, crash records, and rule-violating records, which comprised behaviors such as exceeding the speed limit, driving with one hand, and not pulling over, among others. The authors concluded that the random parameter logit model outperformed the binary logit model statistically. Moreover, the only driver-related variable that produced a random parameter was the "non-at-fault crash record". The authors' interpretation is that while most drivers would be more cautious after a crash, others would not.

The exception is the study of Chouhan *et al.* (2022), which did bring the analysis of motorcycle crash frequency, including factors from the Motorcycle Rider Behaviour Questionnaire (MRBQ) formed by traffic errors (7 items), control errors (13 items), speed violations (3 items), and stunts (9 items). The authors compared the Fixed-Parameter Negative Binomial with a Random Parameter Negative Binomial model. Ultimately, the random parameter model resulted in the best statistical fit, and traffic error and stunt performance were found to be fixed parameters and the main predictors of crashes.

Furthermore, Chouhan *et al.* (2022) reported that the variables gender, control error, and speed violation produced a randomly distributed regression coefficient. The fixed-parameter model did not depict control error and speed violation parameters significantly affecting the rider's crash involvement. Interestingly, the random-parameter model showed a negative association of control error and speed violation parameters with the number of crashes. The authors' interpretation was that the riders with a high control error and speed violation score were more skilled and knowingly performing these risky behaviors. The majority of the 392 respondents were young male riders.

Given the multifactorial causes of crashes and that models considering the DBQ factors intend to analyze several individuals based on variables describing their behavior, applying a random-parameter approach that accounts for variations in the effects of explanatory variables across observations might be more appropriate. That is to say that there may be unobserved factors that affect the sensitivity of the crash probability associated with an individual to varying scores on the DBQ subscales. For instance, despite a driver's self-report of committing risky behaviors such as speeding, driving while on the phone, or overtaking when it is prohibited, it might not always result in a higher probability of crashes due to the provided safe road infrastructure, the driver's high skills, or the low traffic on the road network.

Therefore, an analysis considering the primary individual-level variables (demographic, driving exposure, and DBQ scores) was performed using a random-parameter logit model to investigate their influence on drivers' crash involvement. This novel approach under the DBQ context is expected to allow a better understanding of the DBQ-crash relationship and contribute to the DBQ validity discussion.

6.3. MATERIALS AND METHODS

6.3.1. DRIVER BEHAVIOUR QUESTIONNAIRE

The online questionnaire used in this study was divided into two parts. The first part included socio-demographic questions: age, sex, driver's license ownership, and weekly driving frequency, among others. The second part is from a validated version of the DBQ formed by 20 questions, comprising ten Errors (E), five Ordinary Violations (OV), and five Aggressive Violations (AV). For the complete questionnaire, please see Bobermin et al. (2021).

6.3.2. PARTICIPANTS

A total of 1,321 respondents voluntarily completed the questionnaire, 652 Brazilians living in Brazil and 669 Portuguese residing in Portugal as part of another project. All participants gave their consent to the questionnaire, and their anonymity was ensured. A single database for the two countries was used to validate the DBQ version since major cultural differences in the interpretability of the items were not expected. However, the influence of the variable country was considered later in the Spearman correlations and the random-parameter model, but it was not significant. **Table 6.1** summarizes the main characteristics of the total sample.

Table 6.1: Participant's descriptive statistics

Variables	Description
Age (years)	Range: 18-82; Mean: 32.4; SD:12.6
Sex	Male: 48.4% Female: 51.6%
Weekly driving exposure	one or less: 16.4% two or three times: 19.2% five or four times: 19.8% six or more times: 44.6%
Score E	Min: 0; Máx: 28; Mean: 6.4; SD: 4.58
Score OV	Min: 0; Máx: 22; Mean: 6.5; SD: 4.20
Score AV	Min: 0; Máx: 16; Mean: 3.1; SD: 2.90
Crash involvement	Yes: 17.3% No: 82.7%

6.3.3. RANDOM-PARAMETER LOGIT MODEL

A binary logit random-parameter model was employed to investigate the relationship between drivers' characteristics and the DBQ scores with the associated probability of a self-reported crash.

Since only a few drivers were involved in more than one crash, the assumption of the discrete choice nature of the data is satisfied. In this model, the occurrence of a crash is a binary choice: either the driver was involved in a crash ($Y=1$), or the driver was not ($Y=0$). The explanatory variables are gathered in vector x , and the probabilities are represented in **Equations 1** and **2**.

$$\text{Prob}(Y=1|x) = F(x, \beta) \quad (1)$$

$$\text{Prob}(Y=0|x) = 1-F(x, \beta) \quad (2)$$

The set of parameters β reflects the impact of changes in vector x on the probability. A suitable $F(x, \beta)$ model is assumed, usually considering a normal or logistic distribution. The question of which distribution to use has been widely analyzed, concluding that the two distributions give similar probabilities except in the tails (Ferreira and Couto, 2013; Greene, 2012). Furthermore, in most cases, the choice between these two distributions seems to make little difference (Greene, 2012). After analyzing both distributions in the present study, the logistic distribution (logit model) was selected because a slight improvement in the goodness-of-fit measures was found, giving rise to the model of **Equation 3**. The function $\Lambda(\cdot)$ is a notation commonly used for the standard logistic distribution function.

$$\text{Prob}(Y = 1|x) = \frac{e^{\beta x}}{1+e^{\beta x}} = \Lambda(\beta x) \quad (3)$$

Therefore, the random parameter approach allows the estimated parameters to vary across observations, accounting for potential heterogeneity within the data. The decision about the randomness of the parameters is based on the statistical significance of its dispersion parameter. The major distinction between the random-parameter logit model and the regular binary logit model is the inclusion of covariates for the mean of the random parameters. With that aim, a continuous density function of β is introduced, $f(\beta|\varphi)$, where φ refers to a vector of parameters of that density function (mean and variance). So, the random-parameter binary logit model is formulated as **Equation 4** (Greene, 2012; Schroeder, 2010; Washington *et al.*, 2011).

$$\text{Prob}(Y = 1|x) = \int \Lambda(\beta x) f(\beta|\varphi) d\beta \quad (4)$$

A wide range of density functions can specify the parameters' randomness, although many studies have used a continuous form, such as a normal distribution (Washington *et al.*, 2011). Since the numerical integration of **Equation 4** cannot be derived analytically, the maximum likelihood estimates are usually obtained using simulations with Halton draws, as suggested by Train (Train, 2009). Furthermore, marginal effects can be estimated to describe the relative magnitude between the dependent and independent variables. The values of the corresponding marginal effects obtained for each observation are averaged over the population of observations. The marginal effects result from a one-unit increase in an explanatory variable on the outcome probabilities (Washington *et al.*, 2011).

6.4. RESULTS

Firstly, the correlations between explanatory variables were analyzed. As shown in **Table 6.2** regarding variables from 1 to 6, correlations between explanatory variables were low (<0.5). Female drivers reported slightly more Errors; younger males and the most exposed drivers reported more E, OV, and AV, consistent with previous studies (de Winter *et al.*, 2015). Age and sex were also correlated, a result that is likely a consequence of the sample used in which 60% of the young respondents (18 - 26 yo) were females, whereas 72% of the older respondents (>53 yo) were male. The variable exposure showed a statistically significant correlation with age, sex, E,

OV, and AV scores, although low values (<0.3). The three dimensions (E, OV, and AV) showed significant correlations, the highest being between E and OV, around 0.4.

Furthermore, even though some multicollinearity is expected, especially in nonexperimental data, the methodology applied requires exploratory variables to be independent. Therefore, a variance inflation factor (VIF) test was also performed to check for multicollinearity within the variables in the model. The VIF represents a factor in which the regression coefficient's variance is inflated by the intercorrelation (Greene, 2012). Generally, a VIF greater than 10 indicates serious multicollinearity (Greene, 2012). Results demonstrated that multicollinearity was not a concern (maximum VIF = 1.453) (see **Table 6.2**).

Table 6.2: Correlation analysis and collinearity statistics

Variables	1	2	3	4	5	6	VIF
1. Age	--						1.186
2. Sex	-.204**	--					1.112
3. Exposure	.305**	-.199**	--				1.193
4. Score E	-.018	.063*	.052*	--			1.256
5. Score OV	-.083**	-.104**	.215**	.405**	--		1.453
6. Score AV	.096**	-.138**	.180**	.289**	.375**	--	1.222
7. Crash	-.080**	-.061*	.046*	.063*	.143**	.025	
95%CI (lower, upper)	(-1, -.033)	(-1, -.014)	(-.001, 1)	(.017, 1)	(.097, 1)	(-.021, 1)	

** Correlation is significant at the 0.01 level (1-tailed)

* Correlation is significant at the 0.05 level (1-tailed)

Note: E = Error, OV = Ordinary Violation, AV = Aggressive Violation, CI = Confidence Interval

Secondly, Spearman correlations between all the explanatory variables and crash involvement were also performed to compare the proposed methodology and previous studies (**Table 6.2**, bottom line). The highest correlation with crashes is observed with the Ordinary Violations scores (OV) (0.143), but also with the Error scores (E), although to a lesser degree (0.063). These significant yet small positive correlations between crashes and DBQ subscales follow previous studies (de Winter *et al.*, 2015). AV was not statistically significantly correlated with crashes; however, this might be due to the items included in this dimension and the separation between AV and OV, which will be discussed further in the **Discussion** section. Finally, age, sex, and exposure statistically correlated with crash occurrences, which is also in line with the literature.

Next, the analysis results considering the random-parameter logit model are presented in **Table 6.3**. As already mentioned, the density function of the random parameters can utilize different distributions. In this study, the normal distribution was statistically significant (based on the significance of the standard deviations), and thus it was used. This distribution means that covariates' effects on crash probability vary around the mean for most crashes, and relatively large effects tend to be found for only a few observations.

Furthermore, in the logit models, the magnitudes of the coefficients are not directly interpretable. Therefore, **Table 6.3** presents the averaged marginal effects obtained for each observation and averaged over the population of observations. The marginal effects give the effect that a one-unit increase in an explanatory variable has on the outcome probabilities (crash involvement) while holding all other variables constant. Regarding the indicator variables, marginal effects give the effect of the explanatory variable going from zero to one (Washington *et al.*, 2011).

Table 6.3: Estimated coefficients of the logit model with random parameters

Variable	Estimated value	Standard Error	P[Z>z]	Marginal Effects	Confidence Intervals
<i>Nonrandom parameters</i>					
Age	-.023***	.006	.000	-.003***	(-.034; -.012)
Sex	-.362***	.125	.004	-.052***	(-.607; -.118)
Exposure 02 - two to three times a week	.269	.216	.214	.038	(-.155; .692)
Exposure 03 - four to five times a week	.357*	.213	.093	.051*	(-.060; .774)
Exposure 04 - six or more times a week	.394**	.197	.046	.056**	(.008; .779)
<i>Means for random parameters</i>					
Constant	-1.068***	.263	.000	--	(-1.585; -.552)
Score Errors	.065	.151	.669	.009	(-.232; .361)
Score Ordinary Violations	.263***	.087	.003	.037***	(.093; .433)
Score Aggressive Violations	-.415***	.130	.002	-.059***	(-.670; -.159)
<i>Scale parameters for dists. of random parameters</i>					
Constant	.983***	.098	.000	--	(.0791; 1.175)
Score Errors	.861***	.121	.000	--	(.0624; 1.097)
Score Ordinary Violations	.274***	.055	.000	--	(.167; .381)
Score Aggressive Violations	1.109***	.133	.000	--	(.848; 1.370)

***, **, * Significance at 1%, 5%, 10% level, respectively.

In order to simulate the maximum likelihood estimation of the model, 1,000 Halton draws were used. The model parameters were estimated using NLOGIT 5 (Greene, 2002). The standard binary logit model (not shown in **Table 6.3**) had very similar goodness-of-fit results to the random parameter model. The main difference is that Errors and Aggressive Violations were not significant in the standard model, and only the highest level of exposure (Exposure 04 – drive frequency of six or more times a week) was found statistically significant.

The outcomes in **Table 6.3** must be read concerning the reference categories of the categorical variables. Hence, the reference variables are male for the sex variable and driving once or less time a week (Exposure 01) for the exposure variable. Age, sex, and exposure were set as fixed parameters. The negative coefficient of age means a decline in the probability of self-reported crashes as age increases. The variable sex has a negative coefficient, meaning being female is associated with decreased crash likelihood. Moreover, the differences in the likelihood of crash involvement considering the highest levels of exposure (categories Exposure 03 and 04) compared to the reference category (Exposure 01) shown in the random-parameter model confirmed that drivers who drove more frequently had a higher probability of being involved in a crash. These results are in line with the correlation analysis (**Table 6.3**).

Furthermore, the estimation results shown in **Table 6.3** indicate that the constant term and the three DBQ scores produced statistically significant random parameters (i.e., the standard deviation of the parameter's distribution was significantly different from 0). The constant term has the same meaning as the random-effects approach that assumes that the shared unobserved effects are distributed across the population according to some predetermined distribution (in this case, a normal distribution), and shared unobserved effects are assumed to be uncorrelated with independent variables.

A more detailed look at the data in **Table 6.3** reveals that for the Aggressive Violation score variable, considering a normal distribution with a mean of -0.415 and standard deviation of 1.109, in 35.41% of the observations, an increase in the AV scores resulted in a higher probability of being involved in a crash. However, it reduced this probability in most cases (64.59%).

Concerning marginal effects, **Table 6.2** shows that a unit increase in the AV scores results in an average 0.059 decrease in the probability of a crash.

The Ordinary Violation scores had the greatest effect on the probability of self-reported crashes. In 83.14% of the observations, an OV increment increased the crash probability, while it showed an opposite effect for only 16.86% of the cases. The average marginal effects indicate that a unit increase in the OV scores results in an average 0.037 increase in the probability of a crash. A higher effect (0.143) was found in the correlation analysis.

Finally, the Error scores showed a significant standard deviation (i.e., confirming heterogeneity) but not a significant mean. The interpretation is that positive and negative coefficients in the sample compensate for each other, such that the coefficient of the mean is not significant (Sarrias, 2016).

6.5. DISCUSSION

Concerning the relationship between explanatory variables and crash involvement, age, sex, and exposure were statistically significant for crash occurrences considering the three approaches: Spearman correlation, standard logit model, and random-parameter logit model. In the random-parameter model, all these variables were set to be fixed. The results imply that older, female, and less-exposed drivers reported few crashes, compliant with previous studies (de Winter *et al.*, 2015). Considering that only 3% of the sample is over 60 years old, any increase in crash involvement with age was not expected. On the contrary, considering this age range, only an increase in experience and reduced crash involvement was expected (and confirmed).

Regarding the differences in the results of the three statistical approaches, despite the fixed-parameter and the random-parameter models having very similar goodness-of-fit results, only Ordinary Violation was significant in the former model. At the same time, all three DBQ factors (E, OV, and AV) were significant in the random-parameter model, thus, providing a different perspective of the factors affecting crash involvement in the sample. In the zero-order correlations, it was Errors and Ordinary Violations that were significantly correlated with crash involvement.

Furthermore, the random parameter approach results suggest substantial heterogeneity associated with all individual DBQ scores and self-reported crashes. The Error scores showed a significant standard deviation (i.e., confirming heterogeneity) but with a zero mean coefficient (not significant), probably due to the unobserved heterogeneity among respondents canceling out positive and negative effects. This result supports the idea that errors are not as strong as violations as a predictor of crashes but still can have an effect in some cases. Note that these findings would not be possible to obtain with a logit model with fixed parameters.

Interestingly, the Aggressive Violation – which was not statistically significant either in the Spearman correlation analysis or in the standard logit model – resulted in a lower probability of crash involvement in around 65% of the observations. Consequently, the average marginal effects showed that a unit increase in the AV scores would decrease the crash probability by approximately 0.059. In general, it would be expected that high AV would increase the likelihood of crashes; however, this result suggests that the hostile behavior toward other users might not imply higher involvement in risky situations or the risks may be compensated by other factors (driver's skills, for instance).

As mentioned, careful attention is needed when interpreting and comparing results between studies due to the many diversified terminologies for the DBQ factors connected to the items/behaviors. Firstly, some studies do not always consider Aggressive and Ordinary Violations

separately, while others include only Ordinary Violations in their analysis. Furthermore, although the validated DBQ version employed in this study was based on a traditional one, it contains some differences regarding the traffic behaviors depicted in its items, which must be considered when compared with other studies.

For instance, there are no similar AV items in the study of Chouhan et al. (2022), and considering that the items related to Aggressive Violations in this study include behaviors such as sounding the horn, driving slowly, or getting told by a passenger to calm down, high scores on AV, indeed, might not be expected to implicate real risky situations. On the other hand, this result could also be due to the many other elements that remain overlooked in the analysis, contributing to the high unobserved heterogeneity observed and helping to explain unexpected results, such as in Chouhan et al.'s study, which attributed the unexpected negative association between control error and speed violation parameters with the number of crashes to drivers' skills in their sample.

Finally, the strongest known predictor for crashes, the Ordinary Violation scores, were statistically significant for the Spearman correlation and the standard logit model but also showed heterogeneity across observations in the random-parameter model. In around 20% of the cases, an OV increment decreased the crash probability; however, the average marginal effects indicate that a unit increase in the OV scores resulted in an average 0.037 increase in the crash probability. Despite the general agreement among the statistical methods, this result puts in question the relationship between OV scores and crashes in some cases. Although the OV score can cover some behaviors that affect crash involvement, the resulting unobserved heterogeneity suggests that this explanatory variable's effect varied across the population of respondents. The randomness of the three driver behavior parameters could be due to several factors, such as variability among road infrastructure, weather circumstances, and traffic flow, and not exclusively related to drivers' characteristics, such as driver skill.

From the results of Chouhan et al. (2022) and this study, it can be derived that a considerable number of variables produced random parameters, i.e., many driver-related variables presented unobserved heterogeneity across observations. Undoubtedly, more studies considering random parameters and the DBQ factors are needed to draw further conclusions. Future analysis could benefit by including other exploratory variables related to the environment, traffic, or driver skill to clarify the influence of behavioral history questionnaires, such as the DBQ, on crash occurrence.

6.6. CONCLUSIONS

Over time, many studies point out the larger share of the human factor in crash causation (Dingus *et al.*, 2016; Treat *et al.*, 1979), and studying the relationship between Driver Behavior Questionnaire and crash involvement is a way to understand and measure this share. Several studies repeatedly tested the relationship between DBQ factors and crashes, finding only a small positive correlation between violations and errors with self-reported crashes (de Winter and Dodou, 2010).

However, a critical shortcoming of the methods used in DBQ-crash relationship studies is the assumption of a fixed and unique coefficient for all observations in the sample, which might not be realistic. Thus, the positive coefficient between DBQ scores and crashes might hide significant individual heterogeneity resulting in misleading inferences for subgroups that do not hold the same positive relationship or do not hold the same magnitude of the effect (Sarrias, 2016). Moreover, the heterogeneity among observations could cancel out positive and negative effects, resulting in a non-significant coefficient (Sarrias, 2016). Therefore, a model that allows for individual heterogeneity may be more appropriate.

This study analyzed the relationship between individual characteristics and self-reported crashes using a random-parameter binary logit model. The scores on Errors, Ordinary Violations, Aggressive Violations, and information regarding age, sex, driving frequency, and self-reported crashes of 1,321 drivers were analyzed. The variables age, sex, and exposure were set to be fixed parameters, correlating youth, maleness, and higher exposure to a higher probability of self-reported crashes; however, the results suggest substantial heterogeneity in the relationship between individual DBQ scores and the likelihood of self-reported crashes.

For most of the observations, Aggressive Violations contributed negatively to the likelihood of self-reported crashes, while the opposite was true for Ordinary Violations. The Error score represented the intermediate situation, meaning that the negative contribution cancels out the positive contribution, resulting in a non-significant mean, despite the confirmed heterogeneity (significant standard deviation). These outcomes point out that although the behavioral history variables reflected by the DBQ scores affect the crash occurrence, there is a need to consider other variables in the analysis of crash probability to understand better all the relevant crash-contributing factors and how they intercorrelate.

An important limitation of the study is that a questionnaire was used to assess driving behavior and crash records, which may be unreliable. In order to mitigate this problem, a future study is planned, using a driving simulator to investigate the influence of driver profile (DBQ scores) on driver performance used as a proxy for crash involvement.

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THE INFLUENCE OF MIDDLE-AGED MALE DRIVER PROFILE ON DRIVING PERFORMANCE AND THE EFFECTS OF THREE PERCEPTUAL COUNTERMEASURES: A SIMULATOR STUDY

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The final paper comprehensively analyzes the road-driver interaction captured in a driving simulator experiment and is derived from the outcomes of the other papers. The systematic review (chapter 3) contributed to potential literature gaps and the best practices of driving simulator studies adopted in the experiment. The clustering approach (chapter 4) pointed out the scenario used for the simulation and the characteristics of the subpopulation to be recruited for the experiment. Moreover, participants that met the targeted subpopulation criterium answered the new version of the DBQ proposed in the paper presented in Chapter 5. Finally, the relationship between DBQ scores and crashes initially studied in Chapter 6 was examined on the driver-performance level in this chapter.

This final paper was based on the concept that human characteristics influence road perception and road environment influences driver behavior. Therefore, the interaction between DBQ scores and driver performance was examined through random-parameters models with heterogeneity in the means to accommodate the unobserved heterogeneity across observations.

Furthermore, the interaction between DBQ scores and safety measures was examined. Three low-cost countermeasures that aimed to nudge drivers toward safer behaviors were proposed and studied under the same approach of random-parameters models since their effectiveness might be affected by drivers' interpretation.

Overall, the paper offers some contributions on the theoretical level, allowing a comprehensive understanding of the influence of drivers' profiles on driving performance and, on the practical level, testing countermeasure design alternatives for safety problems similar to the simulated scenario.

ABSTRACT

The human-environment-vehicle triad and how it relates to crashes has long been a topic of discussion, in which the human factor is consistently seen as the leading cause. Recently, more sophisticated approaches to Road Safety have advocated for a road-driver interaction view, in which human characteristics influence road perception and road environment affects driver behavior. This study focuses on road-driver interaction by using a driving simulator. The objective is to investigate how the driver profile influences driving performance and the effects of three countermeasures (peripheral transverse lines before and after the beginning of the curves and roadside poles in the curves). Fifty-six middle-aged male participants drove a non-challenging rural highway simulated scenario based on a real road where many single-vehicle crashes occurred. The drivers' profiles were assessed through their behavioral history measured by a validated version of the Driver Behavior Questionnaire (DBQ) comprising three dimensions: Errors (E), Ordinary Violations (OV), and Aggressive Violations (AV). The relationship between speed and trajectory measures and drivers' profiles was investigated using random-parameter models with heterogeneity in the means. The models' results showed that the DBQ subscale scores in OV explained a considerable part of the heterogeneity found in drivers' performance. Furthermore, the heterogeneity in the means caused by the DBQ subscale scores in OV and E in the presence of peripheral transverse lines indicates a difference in how drivers react to the countermeasures. The peripheral lines were more efficient than roadside poles to moderate speed but did not positively influence all drivers' trajectories. Although the peripheral lines could be seen as an alternative to change driver behavior in a non-challenging or monotonous road environment, the design used in this study should be reviewed.

KEYWORDS: Driver Behavior Questionnaire; Driving simulator; Countermeasures; Random parameter model

7.1. INTRODUCTION

An often-discussed topic in road safety is understanding crash dynamics. Crashes are recognizably rare events where multiple factors play a role; however, the human factor has been consistently claimed as the most important one (Dingus et al., 2016; Treat et al., 1979).

It appears that drivers are often held accountable for crashes because they are the ones who have failed in the ultimate sequence of events, although the wrong stimuli from the road could also have triggered the incorrect driver behavior. For instance, it is already well-recognized that many cues provided by the road design and surroundings influence the driver's speed choice, such as cross-section width or the degree of enclosure caused by vegetation (Anciaes, 2022; Tottadi and Mehar, 2022). Nevertheless, crash prevention efforts, especially in low- and middle-income countries, have often been centered on changing road users' behavior via enforcement, traffic laws, education, and public awareness (Heydari et al., 2019; Hyder et al., 2013; Tavakkoli et al., 2022), denying the road environment's potential to contribute to a more sustainable change in drivers' behavior.

In this regard, the World Road Association (PIARC) promotes the Human Factors concept in its guidelines for a safer man-road interaction, acknowledging that human characteristics influence road perception and road environment influences drivers' right or wrong actions (PIARC, 2016). Studies on crash causation that considered the Human Factors or other holistic perspectives toward road safety indicated that road design factors contributed to up to 70% of the total crashes in some cases (PIARC, 2016; Turner et al., 2016).

The main advantage of adopting a holistic road safety perspective is encouraging crash prevention efforts toward road environment improvements on occasions where the road environment would not otherwise be seen as a problem. In this context, the proposed study investigates the driver performance of drivers with similar features to those most frequently involved in crashes from a Brazilian crash database in a scenario that reproduces road conditions associated with many single-vehicle crashes that, in general, would be easily related to the human factor.

The scenario conveys a non-challenging impression, consisting of a rural highway with shoulders, good road geometry, and low traffic flow during daylight lighting conditions. It has already been pointed out that under similar circumstances, i. e., roads compliant with minimal design standards, studies on crash causation have generally been very conservative in faulting factors other than human, and the road environment has often not been viewed as a potential contributing factor to crashes (Hauer, 2016; Shinar, 2017).

Therefore, considering that the primary goal of the Human Factor concept is to minimize the misleading stimuli potentially given by the road to the drivers, three road safety measures (peripheral lines with different locations and side poles) were tested, focusing on how they affect driving performance. Road countermeasures have been shown to increase safety in numerous situations (Bahar et al., 2004; Donnell et al., 2019; Fitzpatrick et al., 2019; Lyon et al., 2015; Srinivasan et al., 2009) and can be seen as a strategy to change drivers' behavior.

However, not all drivers' actions come from road perception, and there might be differences in how drivers react to the road environment or the countermeasures. Some studies that examined drivers' behavior revealed significant differences due to their profile (Helman and Reed, 2015; Ilkhani et al., 2022; Marengo et al., 2012; Zhao et al., 2012), while others even indicated that individual differences due to stable personality characteristics partially explained crash and near-crash involvement (de Winter et al., 2018; Dorn and af Wählberg, 2021; Engström et al., 2019).

Therefore, we used a validated version of the Driver Behavior Questionnaire (DBQ) (Bobermin et al., 2021) to include drivers' profiles through their behavioral history when analyzing their

driving performance and the effects of the countermeasures. The DBQ was first introduced by J Reason et al. (1990) and has since been one of the most well-known and applied tools for evaluating driver behavior (Bener et al., 2020; Campos et al., 2021; Chaumont Menéndez et al., 2022; Ersan et al., 2020; Farooq and Juhasz, 2020; Han and Zhao, 2020; Shi et al., 2022; Wang and Xu, 2019).

The main goal of this study is to investigate how different drivers' profiles respond to the road environment and road interventions, especially to verify the effectiveness of the countermeasures in changing the behavior of the most at-risk drivers and possible undesirable and unintended effects linked to a particular group, as well as identify any improvements that might be made to the countermeasures to enhance its effectiveness. The analysis was conducted through a set of random parameter models with heterogeneity in the means considering the driving performance (speed- and trajectory-related measures) in four subsections (before curves, curves, after curves, and tangents) observed in a driving simulator. This approach contributed to understanding the interaction between the tested countermeasures and drivers' profiles.

This paper is divided into six sections. The following section, **Section 7.2**, contains the background of previous research findings regarding the countermeasures tested in the driving simulator and the questionnaire used to determine drivers' profiles. **Section 7.3** details the methods applied, from the participants' survey to the model used to analyze the data. **Section 7.4** reveals the compiled results from the twenty-four models, and **Section 7.5** discusses them in light of the previous literature. Finally, **Section 7.6** presents the main conclusions and limitations of this study.

7.2. SCOPE AND BACKGROUND

7.2.1. ROAD SAFETY MEASURES

According to the Human Factors' principles toward road safety, the road environment should be tailored, based on the driver's psychological and physiological limits, to affect how they perceive and react, moving them to improved actions and benefiting safety (PIARC, 2019). The simulated scenario in this study was based on single-vehicle crash records where speeding, fatigue, and inattention were among the Human Factors crash triggers related to road design. However, regarding the road safety practice from the context where the data were obtained (Brazil), there is no standard countermeasure established for these conditions.

In the iRAP Toolkit, road delineation using traffic signs and speed management using road markings are among the most cost-effective and easy-to-implement (even on existing roads) countermeasures suggested for the crash scenario under analysis (iRAP, n.d.). Therefore, this study focuses on two specific countermeasures inside the range of traffic signs and road markings: roadside poles and peripheral transverse lines. These countermeasures were particularly interesting to be tested because they are not consistently applied or associated with any hazard condition, which is relevant as uniformity in traffic signs' appearance and use is essential to avoid misleading drivers and ensure all their benefits for road safety (Department for Transport, 2018).

7.2.1.1. Peripheral Transverse Lines

Peripheral lines/bars consist of transverse pavement markings (typically white) placed perpendicularly to the driving direction to narrow the perceived lane width, promoting traffic alignment by obliging road users to follow orderly and common trajectories. As lane width decreases, driving speeds tend to decrease because of the effort required to steer and maintain position in the lane.

In general, the research on the peripheral lines focused on speed effects, with studies showing positive results in terms of speed reduction (Akbari and Haghighi, 2020; Awan et al., 2019; Calvi et al., 2019; Ding and Jiao, 2021; Godley et al., 1999; Katz, 2007). However, in an observational before-after study, Boodlal et al. (2015) reported that even though minor speed reductions occurred at some locations, the interventions were not effective enough in providing the desired speed limit compliance. The authors suggested future studies to extend the treatment through the curve as the benefits gained by reducing driver operating speeds before the curve may have been lost as drivers compensate and accelerate after the end of the intervention (at the beginning of the curve) (Godley et al., 1999).

Indeed, studies have also focused on the effects of different peripheral line designs on driver behavior. Katz (2007) observed better results in speed reduction in locations with higher contrast between pavement and intervention colors, while for Calvi et al. (2019), peripheral red lines were the most effective in reducing speed.

A typical design variation is decreasing the spacing between lines, usually calculated based on the initial speed (approach speed) and the final desired speed (advisory speed), aimed to create the illusion of traveling faster, thus inducing drivers to slow down. However, Godley et al. (1999) and Katz (2007) found the same effect regarding speed for either decreasing or constant spacing between bars. Fewer studies focused on the effects of peripheral lines on drivers' lateral position in general, but Katz (2007) reported that only in the space-decreasing design did drivers travel significantly further away from the centerline, even though they moved just slightly more to the center of their lane, not enough to avoid driving over the pavement markings (Katz, 2007).

Some peripheral line design variations also showed positive results regarding drivers' lateral position. For instance, Awan et al. (2019) observed that the herringbone pattern (peripheral transverse lines angled at about 45 degrees) applied throughout the curves forced drivers to maintain a safe distance from the opposite lane. Likewise, Akbari and Haghighi (2020) reported that while the peripheral lines and the peripheral hatched markings (adding a longitudinal line inwards from the edge line) made drivers position themselves closer to the center of their driving lane, only with the peripheral hatched markings was a significant reduction of the lateral position found.

The predominant use of peripheral lines has been before curves with lower speed limits (Awan et al., 2019; Boodlal et al., 2015; Calvi et al., 2019; Katz, 2007), although other situations include delimiting the transition from a rural highway to an urban community (Akbari and Haghighi, 2020), on approaching intersections (Godley et al., 1999), and exit ramps (Katz, 2007). Recently, some studies have extended their applications to include other situations.

For instance, in a naturalistic study, Ding and Jiao (2021) investigated the short-, medium-, and long-term performance of the reverse linear perspective markings on driver behaviors. They used yellow instead of the usual white in the road markings, the same spacing between bars but changing the width. The intervention was installed on a 300m straight segment and in the middle of a curve ($R=1208.8$ m) in a two-way-four-lane freeway (100km/h). The authors reported a speed reduction compared to the baseline on both the straight and curve segments that, although weakened over time, sustained some effect (approximately 0.50 m/s in speed reduction) (Ding and Jiao, 2021).

In another recent study, Bassani et al. (2022) used a driving simulator to evaluate two countermeasures along acceleration ramps connecting a rural highway to a curved motorway segment. Three new horizontal markings were implemented along the entire ramp length, including one similar to peripheral lines (the lines decreased in width while their spacing remained equal). The intention was to improve drivers' performance at merging operations. The authors

reported a lower standard deviation of lateral position values produced by the peripheral lines, indicating a positive effect on lateral vehicle control without interfering with vehicle speeds (Bassani et al., 2022).

7.2.1.2. Roadside Poles

Roadside poles, also known as guide posts or post-mounted delineators, are a type of retroreflective vertical sign device (usually white with a reflector at the top) mounted along the side of the roadway in a series to indicate the roadway's alignment. One advantage of side poles is that they do not interfere with the driving lane and do not constitute a roadside hazard as they are usually made of a frangible material.

Delineation can assist drivers in detecting the features of the road, assessing the level of difficulty ahead, and allowing anticipatory control of the vehicle. They are intended to indicate the proper trajectory along the segment, also influencing mental workload and speed perception. Roadside poles are commonly used at horizontal curves, and the spacing between delineators usually follows guidelines considering the radius of the curve, a recommendation based on the intention to keep several delineators in the driver's view at all times, although there are considerable differences in spacings among traffic sign manuals (Campbell et al., 2012; CONTRAN, 2022; MUTCD, 2018).

Overall, the literature regarding road delineation focused on horizontal curves and was developed toward the use of chevron signs rather than roadside poles. However, there are some examples of studies that investigated side poles. One of them is the before-and-after study by Kallberg (1993), which evaluated the effects of reflector posts installed at 60-m intervals on driver performance along roads with lower geometrical standards (80km/h speed limit) and better geometric standards (100km/h speed limit). The author reported that on both roads, the lateral position of vehicles shifted toward the edge of the road; however, regarding speed, drivers increased their speed for the low geometric standard roads, while no significant effects on speed were detected on the high geometric standard roads (Kallberg, 1993).

Godley et al. (1999) also studied reflector posts on rural road curves (Radius = 1000m, speed limit = 100km/h). They tested three new post layouts against the standard configuration of posts (both sides of the curve at constant spacing and distance from the edge of the road). The new configurations were: (i) varied lateral placement of posts on both sides, (ii) varied lateral placement on posts outside of the curve, and (iii) varied lateral placement and height on posts outside of the curve. Results diverged regarding right and left curves, i.e., depending if the driver was on the inside or outside of the curve (left-hand drive), but the third configuration showed the best benefits overall, reducing speed for right curves with no increase in speeds for left curves compared to the standard configuration (Godley et al., 1999).

Chrysler et al. (2005) studied delineator configurations in a field test, where each participant had to drive through curves marked by delineators (radii of 91.4m and 289.5m). Participants were asked to stop the vehicle at different distances from the curves and subjectively assess the degree of the curvature. The configurations under analysis used fixed spacing of delineators in the curve and tested fixed (double the space used in the curves) and variable spacing in the tangent when approaching the curve. The tangent arrangement comprised three delineators.

The authors reported that drivers could not distinguish between variable and fixed spacing on approaches to the curves (Chrysler et al., 2005). The main objective of this study was to support guidelines for delineator applications; thus, the recommendation was that the approach and departure delineator spacings should be fixed at two times the appropriate curve spacing, which is fixed and based on the radius of the curve (Campbell et al., 2012).

In studies focusing on chevron signs, Rose and Carlson (2005) indicated that having more than two chevrons in view around the curve benefited the speed reduction. However, Zhao et al. (2015) raised the issue that this guidance is too vague and difficult for field implementation; therefore, they set a driving simulator experiment using chevron signs at constant spacing (12m) with different curve radii (125, 400, and 1000m). The authors reported a significant effect of chevrons on speed reduction not affected by the radius and a statistically significant effect of chevrons for keeping drivers in a more stable lane position for the large radius curves (Zhao et al., 2015).

More recently, in a driving simulator study, Babić et al. (2022) tested different chevron designs for horizontal curves on rural roads during daytime conditions. The authors pointed out that all of the designs reduced the driving speed; however, the highest speed reductions were observed when signs had a fluorescent background combined with red arrows and a white background combined with black or red arrows. Furthermore, they reported that no significant differences between different chevron designs for the lateral position (Babić et al., 2022).

In summary, similar to the peripheral lines, despite the side poles having shown some positive results influencing driver behavior, their effects may vary depending on the place/situation where they are applied, their position, and their design. Therefore, overall, the literature reinforces the need to test interventions in the specific context before any potential field implementation.

7.2.2. DRIVER BEHAVIOR QUESTIONNAIRE (DBQ)

This study focuses on the driver profile measured by the Driver Behavior Questionnaire (DBQ). The questionnaire was first introduced by Reason et al. and consisted of several items regarding typical traffic situations where drivers must answer how often they had engaged in such behaviors during a specific period (Reason et al., 1990). The authors identified three distinct types of failures related to crashes: violations, dangerous errors, and relatively harmless lapses.

Since then, many other studies replicated the DBQ with slight differences to include culture-specific situations (e.g., religious prohibition of alcoholic consumption), different types of drivers (e.g., professional drivers, motor riders), or updated items (e.g., cell phone use) (Alavi et al., 2016; Ang et al., 2018; Cordazzo et al., 2016; de Winter and Dodou, 2010; Guého et al., 2014; Jomnonkwao et al., 2021; Matawaha et al., 2020; Sârbescu, 2013; Shao et al., 2020; Sucha et al., 2014).

The DBQ version used in this study is a validated version with twenty items divided into three components: errors, ordinary violations, and aggressive violations (Bobermin et al., 2021)(see **Section 7.3.1**). According to the theory proposed by Reason et al., while errors and violations would be potentially dangerous to crash occurrences, lapses would unlikely impact driving safety (Reason et al., 1990).

Many studies that have evaluated driver behavioral history by the DBQ have confirmed the relationship between crashes and errors or violations, although this association is relatively weak (Al Azri et al., 2017; Bener et al., 2020; de Winter et al., 2015; de Winter and Dodou, 2010; Karimi et al., 2022; Shi et al., 2022; Sullman et al., 2019; Wang and Xu, 2019). De Winter et al. (2015) argue that correlations are necessarily small as crashes are rare, especially when analyzed on the subject/person level.

Studies that analyzed drivers' performance patterns as a proxy safety measure for crashes also found differences according to their DBQ scores. Domenichini et al. (2019) studied drivers' speed and the effects of traffic calming measures at pedestrian crossings in a driving simulator considering drivers' profiles. Drivers were divided through a clustering method into three risk profile groups (careful, worried, and at risk) based on their answers to the DBQ and the State

Anxiety Inventory. The authors concluded that the proposed measures effectively reduced the speed of all psychological sub-groups of drivers but with different effectiveness.

The study carried out by Domenichini et al. (2019) highlights a potential drawback of analyzing groups of drivers: grouping participants by high/low DBQ might not fully use the available data (individual scores), making it difficult to isolate the effects of the DBQ sub-scales. Nevertheless, studies generally converged in observing higher speeds related to high ordinary violation scores (Deng et al., 2019; Helman and Reed, 2015; Zhao et al., 2012).

Deng et al. (2019) also reported a correlation between the error subscale with the speed choice tendencies observed in an instrumented vehicle, although slightly lower than with the ordinary violation subscale, while no significant correlation was found with the lapses subscale. Zhao et al. (2012) observed the influence of error scores on speed in an on-road study, but it lost significance when controlling the influence of other variables (including other DBQ subscale scores). For Helman and Reed (2015), who used both an instrumented vehicle and a driving simulator, neither the error nor the lapse sub-scales were associated with drivers' speed.

The driver's trajectory has not been analyzed as much as speed, but Zhao et al. (2012) reported that drivers with high violation scores were likely to have poorer lateral control, change lanes more frequently, spend more time in the left lane, and have more sudden unidirectional accelerations.

In general, studies did not divide scores between aggressive and ordinary violations. However, a recent on-road study by Hill et al. (2023) focusing specifically on speed-related questionnaires evaluated the frequency of drivers' speed-related heavy-braking events and reported that among the standard DBQ scales (all violations, ordinary violations, aggressive violations, and errors), only ordinary violations scores were positively and significantly associated with the frequency of speed-related heavy-braking events.

In summary, the literature demonstrates that drivers' crash risks and driving performances vary depending on their personal characteristics, but only a few studies have considered the driver profile when analyzing countermeasures' effectiveness. Therefore, in the following section, the experimental driving simulator study performed to help close this gap will be explained in detail.

7.3. MATERIALS AND METHODS

7.3.1. QUESTIONNAIRE

The online questionnaire used in this study was divided into two parts. The first part included socio-demographic questions: age, sex, driver license ownership, and weekly driving frequency, among others. The second part is from a validated version of the DBQ formed by 20 questions, comprising ten Errors (E), five Ordinary Violations (OV), and five Aggressive Violations (AV). Examples of these types of behaviors are: underestimating the speed of an oncoming vehicle when overtaking (E), disregarding the speed limit on a motorway (OV), and becoming angered by a certain type of driver and indicating hostility by whatever means the driver can (AV). For the complete questionnaire, please see Bobermin et al. (2021).

Respondents answered how often they had engaged in traffic behaviors during the previous year on a six-point Likert scale between 0 (never) to 5 (nearly all the time). The questionnaire was distributed mainly through the researchers' professional and personal networks by email and instant messaging applications, on social media in general, and by handing out flyers with the survey QR code.

Within the focal group criteria (see **Section 7.3.2**), we tried to expand the survey's reach as much as possible to avoid recruiting homogeneous sample groups (such as university staff). At the end of the questionnaire, respondents who met the criteria established for the focal group were invited to contact the researcher and participate in the driving simulator experiment. All participants gave their consent to the questionnaire and the driving simulator trial.

7.3.2. PARTICIPANTS

The sample consisted of 56 individuals, who were recruited considering the predominant characteristics (age and sex) from a Brazilian crash database which also served as the basis for constructing the scenarios (see **Section 7.3.3**). In this database, 90% of the drivers involved in crashes were male, and most were around 40 years old (age mean of approximately 40 years and a standard deviation of 13 years).

Arguably, the appropriate similarity between the sample and the driving population is hard to achieve due to practical and financial issues. However, looking from the perspective of road safety, including participants with similar characteristics to those more involved in crashes may provide a better understanding of the safety problems and their solutions. Therefore, the focal group for the experiment sought to fit the characteristics identified in the crash database.

The participants consisted of Brazilian male drivers aged between 27 and 53 (age mean of 36 years and standard deviation of 7 years, see the **Supplementary Material, Figure 7.5** for participants' age distribution). Most of them were immigrants who lived in Porto (Portugal) and nearby cities and had a driving license. With this strategy, we not only tailored the experiment to actual conditions but also filtered out or minimized the interferences of confounding factors such as sex, age, and traffic culture (i.e., country) in the experiment.

The final sample characteristics are not identical to those pointed out by the crash database but are similar. Among the sample, 68% drove four or more times a week, 11% drove two to three times a week, and 21% once or less a week. Only five have been involved in an active crash in the past three years. The mean and standard deviation (M; SD) of the DBQ scores for the participants were: Error (0.76; 0.41), Ordinary Violation (1.36; 0.88), and Aggressive Violation (0.88; 0.58).

7.3.3. SCENARIO

The simulated scenario in this study is a combination of crash conditions (road geometry, traffic, time, weather) extracted from a crash database of three Brazilian rural highways. Please refer to Bobermin and Ferreira (2021) for more details about the scenario selection.

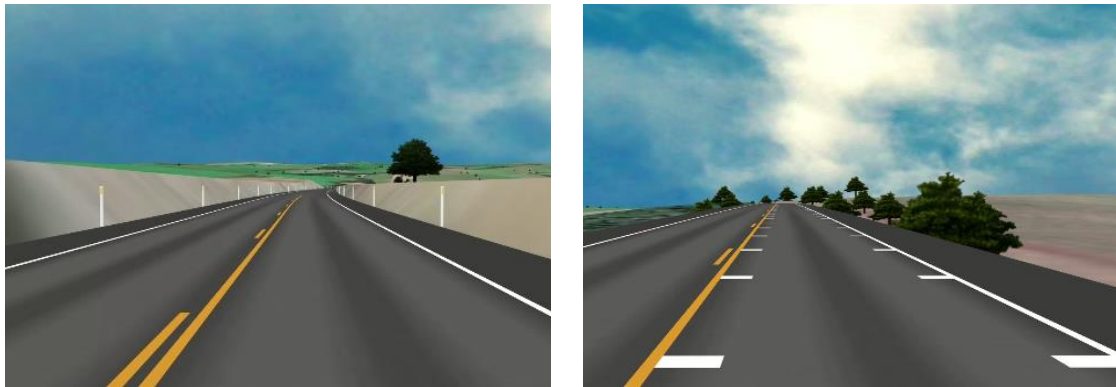
The scenario reproduces an approximately seven km-long segment with gentle curves with a speed limit of 100 km/h (see **Table 7.1**). The cross-section represents a two-lane rural highway (one lane in each direction) with paved shoulders. Typical values of the lane and shoulder were used (3.5m and 1.0m, respectively). Simulated driving occurred in daylight with low traffic flow in the opposite direction (headway of 30 seconds between vehicles). No traffic flow was simulated in the driver traveling direction. The vertical alignment is available in **Table 7.4** as **Supplementary Material**.

Table 7.1: Horizontal geometry

Geometry	Radius (m)	Deflection angle	Direction	Length (m)
Tangent (T) 1				1058
Curve (C) 1	2055.5	9.74°	Right	349
T2				2116
C2	2002	7.75°	Right	271
T3				577
C3	1072.3	8.57°	Left	160
T4				1896
C4	1989.2	8.54°	Left	296

7.3.4. COUNTERMEASURES

Three countermeasures were tested in the driving simulator: roadside poles on the curves (CM2), peripheral transverse lines starting before the beginning of the curves (CM3), and peripheral transverse lines starting before the end of the curves (CM4) (see **Figure 7.1**). The side poles consisted of one-meter-high white posts applied only whitening the curve extension on both sides at a constant distance of 20m for simplicity, considering a potential field implementation.

**Figure 7.1:** Side poles and peripheral lines

The other countermeasures have the same design, just placed in different positions. They are peripheral lines (0.2m x 0.3m) distancing 4 meters between each other also for simplicity in potential field implementation. **Figure 7.6** in the **Supplementary Material** shows the three countermeasures and their location. The peripheral lines covered an extension of 200m. For CM3, they started 150m before the beginning of the curves and ended 50 m after. For CM4, they started 50m before the end of the curves and finished 150m after. CM3 followed a similar location of this type of countermeasure when they were applied before sharp curves, but CM4 was placed where drivers usually start accelerating again after passing a large radius curve (Montella et al., 2015).

Furthermore, two horizontal lines (0.2m x 1.8m) were placed before the peripheral lines' arrangements, combined with a speed limit sign to remind drivers of the speed limit. Speed limit signs were distributed along the segment (one of which was placed at the beginning of the simulation); however, the speed limit before the countermeasures was slightly different, consisting of a rectangular sign with an educational message added to the "regular" speed limit sign (see **Figure 7.7** in the **Supplementary Material**).

The countermeasures' objective was to improve drivers' performance along the whole segment and not particularly in the horizontal curves as they do not demand speed reductions considering

the speed limit of the segment. However, both interventions were placed on and near the curves as we speculated that some performance improvement could arise from the driver anticipating the curve ahead, whether it be a reduction in speed or better lane position (maintaining the vehicle in a central position with the driver's traveling lane). We also avoided placing the peripheral lines in the middle of the tangents considering the possible side effects of that in an overtaking zone, such as adding an excessive or misleading visual stimulus during an already demanding maneuver that requires acceleration and lane changing.

7.3.5. PROCEDURE

The experiment followed a typical protocol consisting of three phases: (i) informing participants about the experiment and participants' consent, (ii) participants' training in the simulator in a different scenario (time free), and (iii) driving the interest case scenario. For the experiment design, a within-subjects (or repeated-measures) study was planned, where all drivers test all four conditions: baseline scenario (without countermeasures), roadside poles (CM2), peripheral lines at the beginning of the curve (CM3), and peripheral lines at the end of the curve (CM4).

The total driving length was about 40km (see **Figure 7.8** in the **Supplementary Material**). The first 10km were intended to promote drivers' adjustment to the road environment, followed by four identical seven-kilometers stretches only differing by the intervention applied: baseline (no countermeasure) and the three countermeasures. These conditions were counterbalanced between participants to ensure equal distribution and diminish order effects.

Participants responded to a simulator sickness questionnaire at the end of the driving session. Drivers did not report any important side effects, and all finished the experiment. However, tiredness, eyestrain, difficulty maintaining focus, and difficulty concentrating were the most cited side effects (around 25% of the sample experienced at least one). In the end, drivers received a maximum value of €20 in a retail voucher for participating in the study.

7.3.6. DRIVING SIMULATOR

The driving simulator (DriS) (Dris Dev Team, n.d.) comprises a fixed-based instrumented Volvo 440 Turbo car, an imaging subsystem with an environment projection in front of the vehicle where images are projected on a curved screen and a sound subsystem intended for motor rotation sound. Due to the early stages of the curved screen operation, the image projected only occupied 3.4 x 2.0 meters of the screen (see **Figure 7.2**). The DriS driving simulator was previously validated on two-lane rural highways, achieving relative validity regarding speed measures, i.e., the simulator results showed the same patterns or effects when compared to real-world driving (Melo et al., 2012).



Figure 7.2: Driving simulator DriS

7.3.7. DATA COLLECTION

Speed and trajectory measures were used as safety indicators regarding driver performance. Speed is recognizably a significant risk factor for crash occurrence and injury severity (Elvik, 2009; Elvik et al., 2019; Nilsson, 1982; Siregar et al., 2023; Tanishita and van Wee, 2017; WHO, 2018). Similarly, an inappropriate lane-keeping performance (invading the opposite driving lane or the shoulder area) or unstable lateral position can also be considered a risk for loss of vehicle control, head-on collisions, or run-off-the-road crashes (Adminaite et al., 2017; Andersson et al., 2006; Charly and Mathew, 2019; Emilia et al., 2022).

Driving data of speed and lateral position were continuously collected with a sampling frequency of 20 Hz. The drivers' performance measures were calculated considering four subsections according to **Table 7.2**. The subsections "Before curve" and "After curve" refer to shorter tangent segments of the entire tangent ("Tang") before and after the curves, respectively, intended to detect local influences that might not appear when analyzing the whole tangent between curves.

Table 7.2: Subsection description

Subsections	Description
Before curve (BFC)	from 100m before CM3 countermeasure to the beginning of the curve
Curve (CRV)	along the horizontal curves
Tang (TAN)	along the internal tangents T2, T3, and T4 (see Table 7.1)
After curve (AFC)	from the end of the curve to 100m after countermeasure CM4

The performance measures analyzed as dependent variables were the speed and standard deviation of speed (Spd and SDSpd) and the trajectory and standard deviation of the trajectory (road axis offset) (Traj and SDTraj) averaged on each of the subsections in **Table 7.2**. In addition, we also computed the number of directional changes (Chang) and the lane violation traveled distance on both sides (DistLV) divided by the total length of the correspondent subsection.

7.3.8. DATA ANALYSIS

In the driving simulator experiment, each driver drove all four conditions (baseline and three countermeasures); thus, we have repeated measurements of the same variable under different conditions on the same subjects. The nature of the performance measures (continuous variables) and the data structure suggested a linear regression approach. The model accounts for the driver and countermeasure effects and their interaction with DBQ scores. Furthermore, it was also desirable to account for the potential heterogeneity due to unobserved factors that may vary across drivers and countermeasure effects; thus, a random parameter regression model with heterogeneity in the means was chosen (William H. Greene, 2012)(see **Equations 1** and **2**).

$$Y_{ij} = \beta_{ij} X_j + \gamma_1 (AGE_i - \overline{AGE}) + \gamma_2 TIME + \varepsilon_{ij} \quad (1)$$

$$\beta_{ij} = \beta_{0j} + \beta_{1jk} (DBQ_i - \overline{DBQ}) + u_{ij} \quad (2)$$

Where i denotes individuals, $i = 1, \dots, 56$; j denotes countermeasures, $j = 1, 2, 3, 4$; and k denotes the DBQ subscales (OV, E, AV), $k = 1, 2, 3$. Y_{ij} is the measured driver performance variable for individual i in countermeasure j . X_j is a dummy variable for each countermeasure. For the sake of convenience, the base scenario is included here as countermeasure 'one' ($j=1$) but represents the model's constant term since β_{i1} is kept for any j in X_j . The terms γ are fixed parameters for the influence of the mean-centered driver's age and time (time represents the condition order as they

were presented to drivers, $t = 1, 2, 3, 4$), and ε_{ij} is the disturbance term assumed to be independently and identically normally distributed with a mean of zero and a constant variance of σ^2 .

The random components, u_{ij} , which we assumed to be normally distributed with a mean of zero and a variance of $\sigma_{\beta_j}^2$, convey the stochastic nature of the random parameters for each countermeasure, capturing unobserved individual- and countermeasure-specific heterogeneity. We also assumed that the random parameters β_{ij} were affected by the individual's mean-centered DBQ scores, with a mean of $\beta_{0j} + \beta_{1jk} DBQ_i$, in which β_{0j} is the fixed mean component, β_{1jk} a row vector of estimable parameters, and DBQ_i a column vector of the three explanatory variables (Errors, Ordinary Violation, and Aggressive Violation scores). The model parameters were estimated by the maximum simulated likelihood method with 200 Halton draws using NLOGIT 5 (William H Greene, 2012).

7.4. RESULTS

The outcomes from the driving simulator trial showed that drivers generally adopted speeds above the speed limit (100km/h). Considering the values recorded in the whole segment (tangents and curves) in the baseline condition, the average speed was 112km/h (SD 28km/h). Indeed, high speeds were expected due to the segment's geometry standards that do not impose speed reductions and the limited realism of simulator experiments that also do not carry the same consequences of crashes or traffic violations.

Regarding drivers' trajectory, a vehicle centered in the middle of the driver's lane would produce a 1.75m offset. Values less than 0.9m or greater than 2.6m indicate that drivers are invading the opposite driving lane and the shoulder area, respectively. Therefore, drivers were generally displaced to the road axis as the vehicles' average trajectory value was 1.52m (SD 0.15m), considering the whole segment (tangents and curves) in the baseline condition.

The influence of the driver profile on driving performance and on the effects of the countermeasures was performed through twenty-four models that were run considering six dependent variables, which describe the driving performance, calculated through four subsections (see **Section 7.3.7**) in four conditions: the baseline condition (B) and the three countermeasures (CM2, CM3, and CM4). A summary of the results is presented in **Table 7.3**, and detailed results of each model can be seen in the **Appendix**.

As can be seen by the models' results, the independent variable age showed a consistent effect throughout the models. By and large, as age increases, the average speed increases while all other variables decrease (the standard deviation of the speed, the average and standard deviation of the trajectory, the number of directional changes, and the lane-violating distance). The exception is the standard deviation (SD) of the speed before curves, where older drivers presented a higher value.

Table 7.3 also indicates that participants drove faster with time (order of the countermeasure) as time had a positive effect in all subsections, while a decrease in speed variability was only observed in subsections BCV and CRV. They also improved their trajectory during curves, positioning themselves more to the center of their driving lane. However, the higher SD of trajectory and directional changes, especially on tangents, suggest that time may have had opposite effects on these geometries.

The constant term was set as a random parameter and consistently confirmed the high heterogeneity expected in driver performance due to unobserved heterogeneity (i.e., the standard deviation of the parameter's distribution was significantly different from 0). The countermeasures

were also hypothesized to be random parameters, as their intended impact might not be achieved or be the same for all drivers. The heterogeneity in countermeasure effects was also confirmed as the standard deviation of the parameter's distribution was statistically different from zero in several models. Therefore, the effect of countermeasures varies significantly for the individuals in the sample.

Taking into account that the model allows interactions between the four conditions (B, CM2, CM3, and CM4) with the three DBQ scores (E, OV, and AV) and the dependent measures were calculated considering four subsections (BFC, CRV, AFC, and TAN), the interpretation of the DBQ scores' influence will focus only on the consistent results, i.e., blocks of shaded areas in **Table 7.3** with repeated similar results.

In essence, the shaded areas in **Table 7.3** reveal that the Ordinary Violation (OV) scores explained a considerable part of the heterogeneity found in drivers' performance measures as they were statistically significant for many of the models (column β_{11}). In contrast, Error (E) and Aggressive Violation (AV) scores were significant factors only for drivers' average trajectory (columns β_{12} and β_{13}). Furthermore, regarding the countermeasures, **Table 7.3** indicates that CM2 only influenced drivers' average trajectory (column β_{02}), while CM3 and CM4 also influenced speed measures and the SD of the trajectory (columns β_{03} and β_{04}). The heterogeneity in the means caused by OV and E scores on average speed (columns β_{31} and β_{41}) and average trajectory (columns β_{32} and β_{42}) in the presence of CM3 and CM4 countermeasures indicates a difference in how drivers react to these countermeasures based on their DBQ scores. The following section will discuss these results further.

Table 7.3: Models' results

Nonrandom parameters			Means for random parameters				Scale parameters for dists. of random parameters				Heterogeneity in the means of random parameters											
Y	Y ₁	Y ₂	β _{0j}				σ _{βj} ²				β _{1jk}											
			β ₀₁	β ₀₂	β ₀₃	β ₀₄	σ _{β1} ²	σ _{β2} ²	σ _{β3} ²	σ _{β4} ²	β ₁₁₁	β ₁₂₁	β ₁₃₁	β ₁₄₁	β ₁₁₂	β ₁₂₂	β ₁₃₂	β ₁₄₂	β ₁₁₃	β ₁₂₃	β ₁₃₃	β ₁₄₃
	AGE ^a	Time	Base/Constant	CM2	CM3	CM4	Base/Constant	CM2	CM3	CM4	Cte/Base_OV ^a	CM2_OV ^a	CM3_OV ^a	CM4_OV ^a	Cte/Base_E ^a	CM2_E ^a	CM3_E ^a	CM4_E ^a	Cte/Base_AV ^a	CM2_AV ^a	CM3_AV ^a	CM4_AV ^a
Spd_Bef	.77855***	1.27985*	104.896***		-6.61468***		16.8534***				3.38496***		-.97361*									
Spd_Curve	1.13357***	1.18415**	107.496***		-6.15102***	-3.78821**	18.8480***	2.10926**	4.06098***	3.10758***	3.50301***		-.98980**	-.67609*	-1.99426***							
Spd_Aft	.69978***	1.04960*	105.272***		-3.63701*	-6.53603***	15.4387***	2.18394**		6.19428***	3.27150***			-1.04852***	-1.68047**							
Spd_Tang	1.21208***	1.37508**	106.004***			-5.43325***	16.5074***	2.24741*			2.57196***			-1.05401***								
SDSpd_Bef	.02322***	-.08125**	1.69900***		1.44503***		.99094***		4.43385***	.32658***			.66579***				-.43224***				.15469***	
SDSpd_Curve	-.03165***	-.11569*	2.04145***		.52797*		.96193***		.37903***	.25093**												
SDSpd_After	-.02259***		1.84149***				.48218***		.14586*	.35843***												
SDSpd_Tang	-.08318***		5.30777***		1.49779***		3.80310***		4.06506***		.36247***											
Traj_Bef	-.00269***		1.56716***	-.05513***	-.05788***		.14044***	.02545**	.05939***				-.01076**		-.01217**		.01556*	.01499*	.01319***			
Traj_Curve	-.00575***	.01095***	1.53024***	-.03314**		-.04815***	.12071***	.03981***	.02609***	.05342***	-.00797***								.00740**		.00812*	
Traj_Aft	-.00549***	.02132***	1.34768***			.10132***	.13441***	.07804***		.10387***	-.00628**		.00870*		-.00980*		.01616**	.01289*				
Traj_Tang	-.00439***		1.50404***	-.02778**	-.03483**		.12921***		.03339***	.02477***			-.00610*		-.01581***		.02131**	.01789***	.00611**			-.00711*
SDTraj_Bef	-.00072**		.09295***		.01316**		.02052***		.01395***		.00267***	-.00419**		-.00286*								
SDTraj_Curve	-.00175***		.17498***		.00896*	.01179**	.03629***	.01785***	.02245***	.01281***	.00252**			-.00238*		.00553**		.00485*				
SDTraj_Aft	-.00097**		.12760***			.02238***	.02766***			.02696***			-.00388*									
SDTraj_Tang		.00635***	.16952***		-.00913*		.03610***	.02692***	.01458***		.00316***											
Chang_Bef		.02211***	.09121***				.04745***	.06431***		.03062***	-.00598***	.00479**								-.00648***		-.00443*
Chang_Curve		.01776***	.04027***				.01948***	.02350***	.01335***	.02383***	-.00219***		.00297***				.00346*					
Chang_Aft		.01836***	.03560***				.02009***		.01230***	.02102***												
Chang_Tang	-.00055**	.02283***	.06021***		-.01050**		.03232***	.03635***	.01716***	.02680***	-.00325***									-.00336**		-.00317**
DistLV_Bef					.01912***		.01416***		.08001***									-.00798*				-.00573**
DistLV_Curve	-.00124***		.02585***				.04937***		.01127***	.01947***	.00363***		-.00355**		-.00780***	.00622*		.00592**				
DistLV_Aft	.00142***		.05377***				.04496***	.06815***	.02045***		.00802***		-.00638**									
DistLV_Tang			.01063***				.01362***		.01590***		.00172**							-.00332*				

Note: ^a mean-centered Age and DBQ scores; ***, **, * Significance at 1%, 5%, and 10% level.

7.5. DISCUSSION

7.5.1. AGE AND TIME EFFECT

The models included the variables age and time to control for their potential influence on the outcomes. The sample in this study was very homogeneous in terms of age to comply with the characteristics of the subpopulation most involved in crashes from a crash database; hence, not much difference in drivers' performance related to inexperience or aging was expected. Overall, the results showed that between the age range studied (27-53 years old), older drivers seem to become more confident or riskier, speeding up and driving closer to the road axis, but they also showed better control of the vehicle, for their lower SD of speed and trajectory, less directional changes, and lower lane-violating distance.

The effects of time, especially the differences observed between tangents and curves, might be explained by Yerkes and Dodson's famous relationship between workload and performance, which says the best performances are reached with a medium level of stimuli. When the stimuli are too low, people will become bored and tired, too high, stressed, and restless (Yerkes and Dodson, 1908). Therefore, the curves might represent an increment in stimulus toward optimum performance. Farahmand and Boroujerdian (2018), when investigating the effect of road geometry on driver fatigue in monotonous environments, also observed a lane positioning ability improvement for scenarios with moderate and high geometric variety.

7.5.2. COUNTERMEASURES

Overall, CM2 had the worst performance among the countermeasures. Roadside poles did not affect driver speed measures and caused drivers to position themselves slightly away from their lane center and to the opposite lane. CM3 and CM4, the peripheral transverse lines layouts, had similar effects to each other, but CM4 (peripheral lines installed after the curves) showed slightly better performances for the case scenario.

For instance, while CM3 and CM4 significantly reduced average speed and affected the area around them, as expected – CM3 had effects on subsections BFC (-6.6km/h), CRV (-6.1km/h), and AFC (-3.6km/h) and CM4 had effects on subsections CRV (-3.8km/h), AFC (-6.5km/h), and TAN (-5.4km/h) – CM4 effects are distinguished because they lasted even considering the whole tangent segment. Furthermore, CM4 effectively reduced speed without increasing the SD of speed, indicating that drivers adjusted their vehicle speed steadier, while CM3 significantly increased speed variability.

In addition, despite all the countermeasures generally caused drivers to move slightly closer to the road axis (around 3 to 5cm), the CM4 effect on the subsection AFT nudged drivers to the center of the driving lane (10 cm), and a slight benefit was also noted regarding CM4 on the TAN subsection, where a small decrease in the standard deviation of trajectory was detected. Therefore, the CM4 seems a promising countermeasure alternative to change driver behavior in a non-challenging or monotonous road environment like the simulated scenario of this study.

Arguably some improvements could be made to the roadside poles to improve their efficacy, such as adopting a more eye-catching color (e.g., orange instead of white), increasing width, extending their application beyond the curve, and decreasing spacing. However, the results suggest that just stressing the curve alignment with the delineators did not change driver speed behavior; drivers seemed to see them just as obstacles and moved away (and to the opposite lane). Therefore, the role of the peripheral lines in providing a sense of constraint directly on the driver's path appears to be of critical importance, especially for speed.

Nevertheless, especially regarding trajectory, the layout of the peripheral lines used in this study should probably be reviewed to focus more on the road axis. The drivers consistently positioned themselves closer to the opposite lane throughout the road alignment; for unclear reasons, some subjects even drove closer to the opposite lane in the presence of peripheral lines. Therefore, some alternatives could be applying visual interventions only on the road axis side, an asymmetrical pattern of the peripheral lines (longer on the road axis side), or peripheral lines with increasing width on the road axis side to explicit the intended movement the drivers should make. Furthermore, although there is no difference in the advisory speed between curves and tangents in the case scenario, longitudinal width increments of the peripheral lines (and thus decreasing space between lines) could also be tested to verify their effects on trajectory due to the sense of constraint that they might provoke with potential improvement in speed reduction as well.

A final discussion is regarding the general magnitude of the effects. The results of speed and trajectory are in line with previous studies, which pointed out speed reductions from 3km/h (Zhang et al., 2023) to 19km/h (Akbari and Haghighi, 2020) and trajectory changes of 5cm (Akbari and Haghighi, 2020) for peripheral lines. Furthermore, the effect for some drivers was even higher because the drivers' profile was incorporated in the analysis, and, as will be seen in the following section, they influenced the countermeasures' effectiveness.

7.5.3. DRIVER PROFILE

The DBQ Ordinary Violation score was predominantly significant to the baseline condition, indicating that OV scores captured differences among drivers related to their driving performance. They convey an image of overconfidence as OV drivers drove faster and steadier, but their trajectory was inferior (high SD of trajectory and lane violation distance).

Other studies also observed higher speeds related to high OV scores (Deng et al., 2019; Domenichini et al., 2019; Helman and Reed, 2015; Zhao et al., 2012) and a positive correlation between the standard deviation of the steering wheel position and violation scores (Zhao et al., 2012), which agrees to some extent with our findings.

High AV scores were related to drivers moving toward the center of their driving lane, a safer maneuver. This association might be unexpected; however, it can be explained by differences in DBQ versions and the fact that studies usually do not divide scores between Aggressive and Ordinary Violations, as done in this research.

For instance, the study by Hill et al. (2023), which applied a similar DBQ version, also showed corresponding results since AV was not related to speed-related heavy-braking events as OV was. However, caution is needed when comparing these studies' results due to the discrepancy between their sample (young female drivers) and this study's sample (middle-aged male drivers).

Furthermore, a previous study that analyzed the crash liability and DBQ scores relationship and used the same DBQ version of this research pointed out that the AV score resulted in a lower probability of crash involvement in most of the observations (Bobermin and Ferreira, 2022). Therefore, despite AV being related to safer driving performance, which is contrary to expectation, it is in accordance with previous findings that used a similar or identical version of the DBQ, reinforcing the idea that the hostile behavior toward other road users measured by the AV scores is not translated into riskier driver's performance.

The Error scores were also significant only to the average trajectory. The higher the Error score, the closer drivers would move to the center of the road axis (and to the opposite lane). In fact, Error scores were consistently related to the average trajectory not only in the baseline scenario but in the presence of the countermeasures, which indicates that drivers' average position might

be more related to drivers' misjudgments or failures of observation connected to their cognitive processes, according to Reason's et al. behavioral theory (Reason et al., 1990).

All the remaining trajectory measures were influenced only by the OV scores, highlighting the central role played by OV. Following Reason's et al. behavioral theory (Reason et al., 1990), the effect of OV on SD of the trajectory, lane-violating, and number of directional changes can be interpreted as drivers' overconfidence with increasing OV scores, deliberately lane-violating (positive effect on SDTraj and DistLV), and not trying to correct their trajectory (negative effect on Chang).

The influence of DBQ scores on the countermeasures' effects was restricted to the effect of OV on average speed and E on the average trajectory but indicates that drivers with different DBQ scores react differently to the countermeasures. Overall, the countermeasures CM3 and CM4 significantly reduced driver speed regardless of the DBQ scores, but this effect was greater for high OV drivers, a similar outcome to Domenichini et al.'s (2019) study on pedestrian crossing countermeasures. **Figure 7.3** shows that the speed reduction effects of the peripheral lines for high OV drivers can be up to 18km/h.

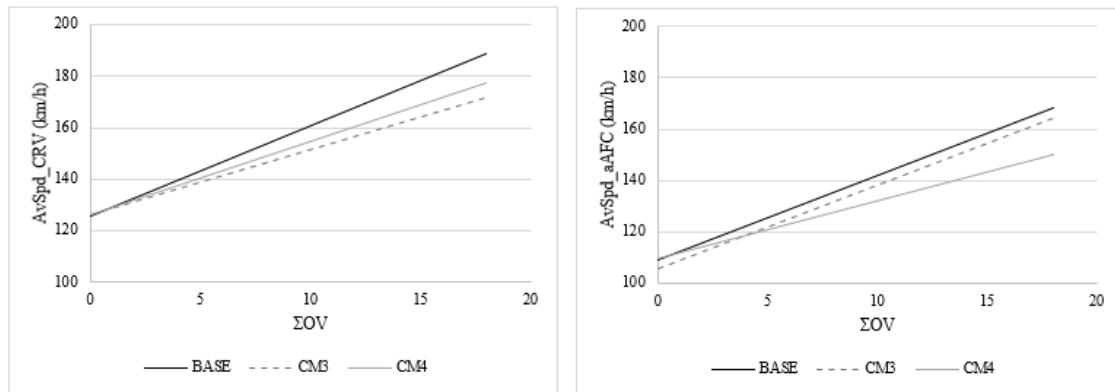


Figure 7.3: Models' results of the average speed (km/h) on curves (left) and after curves (right), considering Age= 36yo, Time=1; the sum of error scores (ΣE), and the sum of aggressive violation scores (ΣAV) at their means

On the other hand, in general, all the countermeasures tested caused drivers to move slightly closer to the road axis, except for high E score drivers who, in the presence of CM3 and CM4, corrected their trajectory and moved to the center of their driving lane (**Figure 7.4**), with changes in trajectory up to 18cm. Therefore, CM3 and CM4 seem efficient for this type of driver profile but have an adverse effect on drivers in general.

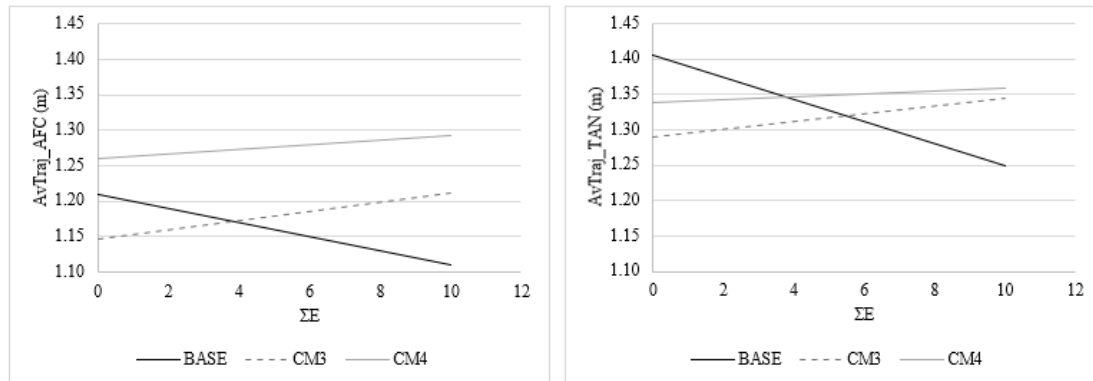


Figure 7.4: Models' results of the average trajectory (m) after curves (left) and tangents (right), considering Age= 36yo, Time=1; the sum of Ordinary Violation scores (ΣOV), and the sum of Aggressive Violation scores (ΣAV) at their means

7.6. CONCLUSIONS

This study focused on road-driver interaction by using a driving simulator. The aim was to test the efficiency of the three perceptual countermeasures (peripheral transverse lines with different locations and roadside poles) for a non-challenging rural highway where many single-vehicle crashes occurred and investigate how personal characteristics measured by the DBQ influence driver performance and countermeasures effects.

We applied a random parameter approach with heterogeneity in the means to model drivers' performance in terms of speed and trajectory. The results suggest that the peripheral transverse lines were more efficient in improving driver performance than the roadside poles. Furthermore, the DBQ subscale scores in Ordinary Violation (OV) explained a considerable part of the drivers' driving performance differences.

Driver profile also influenced the countermeasure effectiveness in some cases: for moderating speed, peripheral lines seem to benefit all drivers, particularly those associated with higher speeds (high OV drivers); regarding trajectory, countermeasures did not have an overall beneficial influence, leading drivers to the road axis, although the subgroup of high E drivers did correct their trajectory in the presence of peripheral lines, positioning themselves more to the center of their driving lane.

Overall, CM4 (peripheral lines installed after the curves) showed slightly better performances for the case scenario and represented the best alternative among the countermeasures. Ideally, final results on the safety effectiveness of the countermeasures should be established with field research, also including long-term effects; however, the driving simulator experiment and the relative differences found among countermeasures serve as preliminary research to indicate countermeasures layouts with a high possibility of success for subsequent design improvements before field tests.

Nevertheless, it is essential to highlight certain limitations associated with this research. One limitation arises from the apparent shortcomings of using a driving simulator that is not entirely realistic. However, the DriS driving simulator has been previously validated on two-lane rural highways, achieving relative validity regarding speed measures, i.e., the simulator results showed the same patterns or effects when compared to real-world driving (Melo et al., 2012). Therefore, although the results likely do not reflect a translation of the absolute values, for this research purpose, focused on the effect of independent variables on driving behavior, it does not affect the overall conclusions as the essential aspect is that the same patterns or effects are observed in real-world driving.

Another limitation is regarding the selected sample consisted of 56 middle-aged male subjects. This research focused on the driver subpopulation characteristics from a crash database; therefore, already restricted. Additionally, the participants were not selected using a statistical criterion, and the sample consisted of people voluntarily willing to participate in the study, configuring a non-probabilistic sample. Consequently, the results cannot be extrapolated to the population, whether the subpopulation from the crash database or the general population. Hence, to corroborate this study's findings, additional analyses on larger samples that also include other driver groups (such as female, younger, and older drivers, etc.) are required.

In addition, this study relies on self-report measures to assess personal driving characteristics, which can be subjected to memory and participant response biases. Nonetheless, drivers were given the assurance of anonymity in their responses to lessen some potential bias. Furthermore, as shown in the literature review, behavioral research often uses self-report data due to its affordability, and several studies have used this methodological approach. Nevertheless, future

studies should consider alternative and supplementary methodological approaches to confirm this study's findings.

Likewise, future research is encouraged to include additional data sources such as brain activity, eye tracking, body temperature, heart rates, or post-questionnaires and interviews to better understand how drivers process the countermeasures. Although road interventions might not significantly alter driving performance, drivers may be more alert and engaged in driving activity due to them. Therefore, including physiological and subjective measures in the analysis could reveal this potential effect and provide insights into the drivers' perception and reaction mechanisms.

SUPPLEMENTARY MATERIAL

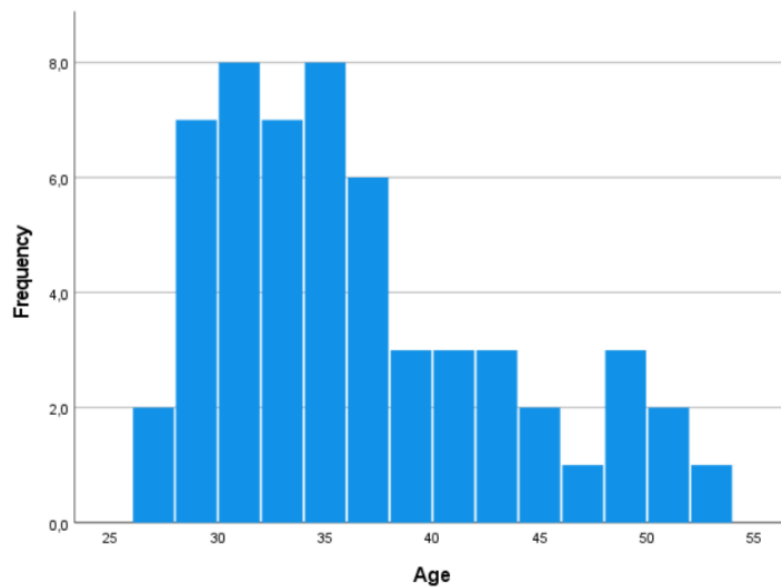


Figure 7.5: Age histogram of drivers participating in the driving simulator experiment

Table 7.4: Vertical alignment

Vertical								
Horizontal (km)	km (initial)	km (final)	Type	Length (m)	Grade (%)	E (m)	A (%)	k (m)
0 start	-0.365	0.505	curve	870		-7.896	-7.2843	-119.43
	0.505	0.9	ramp	395	-3.9624			
	0.9	1.11	curve	210		0.389	1.4812	141.77
	1.11	1.705	ramp	595	-2.4811			
	1.705	1.875	curve	170		-0.575	-2.7075	-62.79
	1.875	2.105	ramp	230	-5.1886			
	2.105	2.285	curve	180		1.236	5.4943	32.76
	2.285	2.51	ramp	225	0.3057			
	2.51	2.83	curve	320		0.507	1.2667	252.62
	2.83	2.97	ramp	140	1.5724			
	2.97	3.11	curve	140		0.386	2.205	63.49
	3.11	3.32	ramp	210	3.7774			
	3.32	3.69	curve	370		-2.256	-4.8816	-75.8
	3.69	3.77	ramp	80	-1.1042			
	3.77	4.09	curve	320		2.374	5.9357	53.91
	4.09	4.23	ramp	140	4.8315			
	4.23	4.95	curve	720		-5.642	-6.2738	-114.76
	4.95	5.15	ramp	200	-1.4423			
	5.15	5.53	curve	380		0.62	1.3053	291.12
	5.53	5.57	ramp	40	-0.137			
	5.57	5.84	curve	270		-0.338	-1.0015	-269.6
	5.84	5.97	ramp	130	-1.1385			
	5.97	6.22	curve	250		1.994	6.3815	39.18
	6.22	7.165	ramp	945	5.243			
7.42 end	7.165	7.525	curve	360		-3.332	-7.4053	-48.61

Note:

E = vertical offset at the VPI (Vertical Point of Intersection)

A = algebraic difference in grade

k = horizontal distance along which a 1% change in grade occurs on the curve

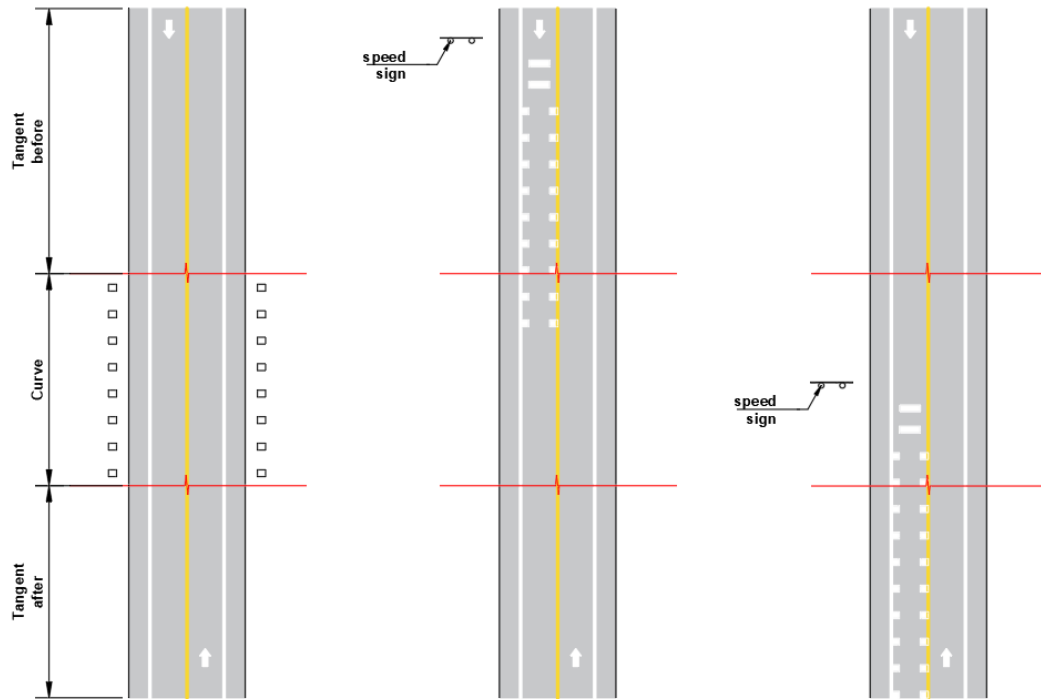


Figure 7.6: CM2, CM3, and CM4 Countermeasures' sketch (from left to right)



Figure 7.7: “Regular” speed limit sign (left) and speed limit sign placed before the peripheral line countermeasures (right) depicting the “regard the speed” message

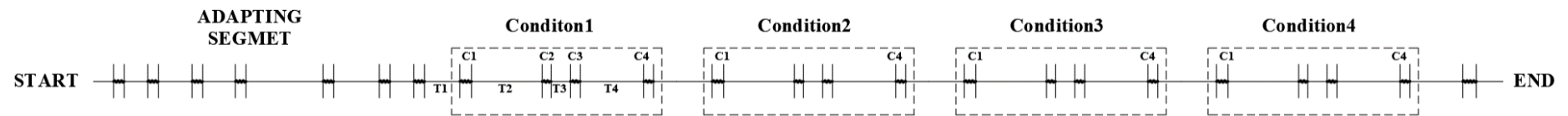


Figure 7.8: Linear sketch of the simulated road segment with all four conditions.
Horizontal curves are in bold, delimited by vertical lines.
T1 = Tangent 1, C1 = Curve 1

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8

CONCLUSION

Road safety is a central issue in managing road infrastructure networks and has strategic importance in any nation's development. However, high rates of fatal crashes and severe injuries are still an unreasonable toll many countries pay for their transport mobility. This scenario is even more disproportionate when looking at numbers from middle- and low-income countries.

Crashes are relatively rare events with a recognizable share of randomness, but there are also identifiable contributing factors to that equation. Therefore, a more mature road safety strategy claims a holistic perspective that considers all the factors.

This study focused on road-driver interaction, ultimately put to the test in a driving simulator experiment. This tool enabled testing and comparing existing and new road configurations, controlling confounding variables, reproducibility of the experiment for each participant, ease of data collection, and, above all, without engaging drivers in dangerous activities. Through the development of this work, many practical contributions to driving simulator experiments were addressed and subsequently followed.

Accordingly, scenario development and participant recruitment were especially given attention, taking advantage of crash databases. The human factor was incorporated through the driver's behavioral history measured by a new and validated version of the Driver Behavior Questionnaire (DBQ), a traditional tool in road safety studies adapted to the purpose of the research. Moreover, a random-parameters model examined the relationship between the DBQ and crash probability to gain new insights into this matter.

All these elements were taken into account in the driving simulator experiment, which measured driver performance in a rural highway scenario considering drivers' profiles. Three countermeasures were tested as mechanisms to influence drivers' behavior. In the end, a comprehensive analysis was delivered with practical and theoretical contributions to understanding driver-roadway interaction. The main findings, contributions, limitations, and suggestions for future research are presented in detail in the following sections.

8.1. KEY FINDINGS AND CONTRIBUTIONS

Overall, this thesis contributes to the research line of road safety in the context of rural roadways by comprehensively analyzing human-driver interaction. During the research development, methodologies and guidelines were produced and disseminated through research papers. The thesis is built from the junction of these papers, but each one of them is an individual work that stands on its own, adding a unique contribution to the final document. The main findings and contributions to answering the research questions proposed by this thesis are summarized in the following paragraphs.

The first set of papers *Driving Simulator for Evaluating the Effects of Road Geometric Design on Driver Behavior*, protocol and systematic review (papers 1 and 2), addressed **RQ 1** «How is the road-driver interaction being studied by experiments with driving simulators, and how do their findings relate to road safety literature gaps?».

The systematic review of the literature (paper 2), which included 34 studies that focused on road geometry features influencing driver performance, identified best practices, potential sources of bias, and typical deficiencies in reporting. Notably, the studies evolved with time but considering that many aspects of the experiment's protocols can influence the results, these issues were discussed and critically appraised. Moreover, a compilation of suggestions for improving driving simulator experiments was provided.

These outcomes were achieved with the aid of the tailored quality assessment tool for driving simulator experiments developed in paper 1. The assessment tool based on the Health Care field standards focused on technical experiment practices and synthesized a list of essential items that could influence studies' results. Careful observation of those items can elevate the quality of the overall research. Therefore, both papers provide valuable tools and knowledge for driving simulator experiments in general.

Paper 2 also delivered a summary of the knowledge produced by driving simulator studies on road geometry's influence on driver behavior put into perspective against the general road safety research findings. Despite the heterogeneity between studies, especially concerning outcome measures, a synthesis compiling the evidence obtained by studies was possible, identifying gaps in road safety knowledge where the potential of driving simulators could be applied in the development of future research.

The third paper, *A Novel Approach to set Driving Simulator Experiments based on Traffic Crash Data*, answered **RQ 2**, «How to identify potential risky conditions considering crash data for a driving simulator experiment, reaching a balance between diversity and specificity?». The paper offered an alternative to support the definition of driving simulator experiments based on crash data.

The method based on Clustering Analysis (K-medoids), suited to deal with the categorical and numeric variables from typical crash databases, was used to reduce the diversity of the data into a set of test scenarios, balancing the homogeneity within the clusters (similarity between crash conditions) and diversity (four scenarios represented the diversity of crash conditions). The proposed method can be seen as a compromise between case-specific and factorial design methods for defining scenarios.

Paper 3 also took full advantage of the traffic crash data to determine drivers' characteristics to participate in the driving simulator experiments, acknowledging that drives involved in crashes are of interest for road safety research. The results from this paper served as input for the driving simulator experiment performed within the scope of this thesis but also highlighted the importance of considering the characteristics of the population at-risk in road safety research.

The fourth paper, *New Version of Driver Behaviour Questionnaire to investigate Driver Behaviour on Rural Roads*, responded to **RQ 3**, «How to measure drivers' profiles considering this thesis' subpopulation and scenario of interests?». This paper tackled a critical point in the research: incorporating driver profiles. Considering that human characteristics influence road perception and road environment influences driver behavior, a tool to explain differences in drivers' behaviors when driving was primary to understand driver-road interaction.

Paper 4 presented a newly validated Driver Behavior Questionnaire (DBQ) adapted to the purposes of the thesis, including rural road situations, modern habits, and considering local culture to identify drivers' profiles. The proposed version was based on a popular version of the DBQ and presented a factor structure, reliability, and internal consistency indices compatible with the traditional version of the DBQ.

Furthermore, paper 4 was essential to disclose the DBQ items and discuss the importance of the question's meaning in interpreting the results. Therefore, not only the items in English and Portuguese were published but also a humble contribution to this research field was conveyed through a summary review of the Portuguese and Brazilian DBQ versions and a concise description of one of the most popular versions: the 28-items DBQ by Parker et al. (1995) and Lawton et al. (1997).

Another contribution from the thesis is regarding the relationship between drivers' profiles and crash occurrences, as stated in **RQ 4**, «How are the drivers' profiles and crash occurrences related?». Research in this field has been done generally through zero-order correlations and assuming that parameters are fixed across observations. However, considering the multifactorial nature of crashes and the inherent heterogeneity expected when analyzing behavioral variables, a random-parameters model was applied in the fifth paper, *Evaluating Individual Heterogeneity in the Probability of Crash Involvement*.

The random-parameter approach allowed the model to account for unobserved heterogeneity across individuals and extract more information from the database, uncovering the relationship considering the new DBQ version. The analysis benefited from the 1,321 questionnaires gathered, and the sophisticated statistics applied, in line with the theory assumed and the nature of the data. The results revealed that the behavioral history variables affected crash occurrence heterogeneously; therefore, considering other variables in future crash analyses was suggested to understand better all the relevant crash-contributing factors and how they intercorrelate.

Paper 6, *The Influence of Driver Profile on Driving Performance: A Simulator Study*, provided a comprehensive analysis of drivers' performance taken as a surrogate measure to crashes and contributed to answering **RQ 5**, «To what extent do drivers' profiles influence driver performance?», through a driving simulator experiment in line with the best practices and focusing on road-driver interaction. Fifty-six participants compliant with the target subpopulation drove the simulated scenario selected based on crash data. The random-parameters models with heterogeneity in the means contemplated aspects of the driver profile, endorsing the DBQ as a measure of driving style, especially regarding the Ordinary Violation scores, since they explained a considerable part of the heterogeneity found in drivers' performance measures.

Paper 6 also acknowledged **RQ 6**, «Do drivers respond differently in terms of performance to road environment changes based on their profiles?». Three countermeasures were tested to change driver behavior, avoiding fatigue and moderating speed. The suggested countermeasures considered practical aspects of their application, and recommendations for future new countermeasure designs for non-challenging or monotonous road environments similar to the one tested were made.

8.2. LIMITATIONS AND FUTURE RESEARCH

As mentioned before, the thesis is built from the junction of research papers, but each one of them is an individual work; therefore, its specific limitations have already been discussed in the previous chapters. In this final summary, the discussion focuses on guidelines for future research considering the significant and transversal limitations and the overall proposed scope of this work.

Firstly, the scope of this thesis, including the definition of simulated scenarios and posterior statistical analyses, was restricted to data from single-vehicle loss-of-control crashes where presumably, road geometry and its interaction with the driver had potentially played a significant role. In addition, the data regarding road characteristics available for this work was limited to only part of three roadways. Focusing on limited crash cases reduces the generalization of the results, and the expansion of the databases can reveal different risk scenarios worth analyzing. Furthermore, the records on driver characteristics involved in crashes were highly homogeneous, preventing some aspects, such as the role of age and gender, from being better examined.

Undoubtedly, the analysis developed in this thesis would have benefited from richer and more precise databases regarding crashes, road inventory, and traffic volume. Nevertheless, despite the limited data, paper 3 (*A Novel Approach to set Driving Simulator Experiments based on Traffic Crash Data*) identified four risk scenarios, although only one was analyzed in the driving simulator. Therefore, an evident expansion of this work is considering the other scenarios in future driving simulator experiments.

Another critical limitation regarding the generalizability of the results is the samples' representativeness. This thesis focused on the driver subpopulation from the available crash database; therefore, already restricted, as previously discussed. Additionally, this research relied on data from 1,321 people who responded to the e-survey (papers 4 and 5 – *New Version of Driver Behaviour Questionnaire to investigate Driver Behaviour on Rural Roads* and *Evaluating Individual Heterogeneity in the Probability of Crash Involvement*) and the 56 participants who engaged in the driving simulator experiment (paper 6 – *The Influence of Driver Profile on Driving Performance: A Simulator Study*). In both cases, the participants were not selected using a statistical criterion, and the samples consisted of people voluntarily willing to participate in the study, configuring a non-probabilistic sample. Consequently, the results cannot be extrapolated to the population, whether the subpopulation from the crash database or the general population.

As the thesis revealed, the subpopulation involved in the crash cases deviated regarding age from the widely known worldwide figures, which usually point out higher young male involvement in road traffic mortality. This outcome emphasizes that different subpopulations are at risk depending on the context, and it is believed that, from a road safety perspective, this subpopulation's particularities are worth analyzing. Therefore, the characteristics of the people involved in the crashes were considered when inviting participants to the driving simulator experiment. However, the characteristics were limited to the available database information regarding drivers (gender and age), which, although configuring important features, it is acknowledged that other aspects, such as the socioeconomic status of drivers, could have provided meaningful insights into the analysis.

Another point regarding papers 4, 5, and 6 is that they also relied on self-report measures. Arguably, self-report measures can be subject to memory and participant response biases; however, participants were guaranteed anonymity in their responses, and the ones that participated in the driving simulator experiment did not respond to the questionnaire immediately before engaging in the driving activity but well before the experiment. Furthermore, behavioral research often considers self-report data and several traffic safety studies have used the driver behavior questionnaire to assess driver behavior. Nevertheless, future studies are encouraged to consider other methodological approaches to reduce biases when measuring drivers' profiles, providing a better estimate of the variables' contribution. Future research in this line will probably benefit from a multidisciplinary perspective, especially in psychology.

An obvious limitation of the research is using a driving simulator (paper 6). The simulated environment can never perfectly reproduce real-world scenarios or drivers' motivation, affecting drivers' responses. Undoubtedly, fix-based simulators can lack the source of cues about the vehicle's motions, but the simulator displays visual cues that are also critical components of the driver's perceptions, providing a satisfyingly immersive experience. Furthermore, paper 2 (*Driving Simulator for Evaluating the Effects of Road Geometric Design on Driver Behavior: A Systematic Review*) listed many examples of the successful use of driving simulators, addressing a wide range of research questions, especially when the aim is to contrast different scenarios, like the comparisons made between countermeasures in paper 6.

In addition, the DriS driving simulator used in the experiment has been previously validated regarding drivers' speed on two-lane rural highways (Melo et al., 2012), which was this thesis's main driver performance measure studied. Nevertheless, naturalistic studies will undoubtedly capture the human-road interaction better and could also include important factors related to the vehicle and the in-vehicle technology role in the analysis.

Finally, the thesis included the Driver Behavior Questionnaire in the driving simulator analysis through random-parameters models, representing an advance in the interdisciplinary approach and methodological sophistication needed in this field. The models focused on driver performance since the interest was in their actions independent of how they felt or interpreted the environment. However, different outcome measures, besides speed and lateral position, could have been considered. Physiological or subjective measures, for example, could have provided information about drivers' intentions/interpretations, which might not have been translated into actions due to the lack of ability or physical limitations. A deeper psychological perspective on this subject would be an interesting asset for future research.

Overall, this research demonstrates the importance of driver-road interaction in road safety. The thesis contributes theoretically and practically to the researched area, shedding new light on contributing crash factors considering the personal characteristics of drivers and showing the potential of changing the context in which risky behaviors occur to nudge drivers to behave safely. As a final remark, it is worth mentioning that it is foreseeable that technology will play an increasing role in road safety, especially related to vehicle technology; however, such individual-level solutions come with a cost, and not everybody will have access to it. Therefore, this research highlights an essential aspect of focusing on human-road-related risk factors: road environment improvements and their interaction with drivers are crucial to guaranteeing a more equitable and safe transport system that embraces all road users.

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Appendix

Models' Results

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 Random Coefficients LinearRg Model
 Dependent variable AVSPD_B
 Log likelihood function -849.11258
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = 1744.2 AIC/N = 7.787
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	.77855***	0.07514	10.36	0	0.63128	0.92583
TIME	1.27985*	0.67447	1.9	0.0578	-0.04208	2.60178
Means for random parameters						
Constant/BASE	104.896***	2.60113	40.33	0	99.798	109.994
CM2	-1.80891	3.22457	-0.56	0.5748	-8.12894	4.51112
CM3	-6.61468***	2.12367	-3.11	0.0018	-10.77699	-2.45237
CM4	-3.44594	2.56456	-1.34	0.1791	-8.47239	1.58051
Scale parameters for dist. Of random parameters						
Constant/BASE	16.8534***	0.47178	35.72	0	15.9287	17.7781
CM2	0.66916	1.27374	0.53	0.5993	-1.82734	3.16565
CM3	1.43309	1.14573	1.25	0.211	-0.81251	3.67868
CM4	0.80658	1.33754	0.6	0.5465	-1.81495	3.4281
Heterogeneity in the means of random parameters						
BASE_C_OV	3.38496***	0.3246	10.43	0	2.74876	4.02117
BASE_C_E	-1.30812	0.85274	-1.53	0.125	-2.97945	0.36321
BASE_C_AV	-0.43314	0.55325	-0.78	0.4337	-1.5175	0.65121
CM2_C_OV	-0.60729	0.68512	-0.89	0.3754	-1.95009	0.73552
CM2_C_E	0.72292	1.92162	0.38	0.7068	-3.04338	4.48922
CM2_C_AV	0.07578	1.33559	0.06	0.9548	-2.54192	2.69348
CM3_C_OV	-.97361*	0.57429	-1.7	0.09	-2.09921	0.15198
CM3_C_E	1.1008	1.21973	0.9	0.3668	-1.28982	3.49142
CM3_C_AV	-0.06889	0.73742	-0.09	0.9256	-1.51421	1.37643
CM4_C_OV	-0.73831	0.55294	-1.34	0.1818	-1.82204	0.34543
CM4_C_E	0.43054	1.09293	0.39	0.6936	-1.71156	2.57265
CM4_C_AV	-0.07717	0.72969	-0.11	0.9158	-1.50734	1.353
Variance parameter given is sigma						
Std.Dev.	7.29703***	0.29176	25.01	0	6.72519	7.86887

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

C_ ==> Mean-centered
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 Random Coefficients LinearRg Model
 Dependent variable AVSPD_C
 Log likelihood function -830.38284
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = 1706.8 AIC/N = 7.619
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	1.13357***	0.06308	17.97	0	1.00994	1.2572
TIME	1.18415**	0.54681	2.17	0.0303	0.11243	2.25588
Means for random parameters						
Constant/BASE	107.496***	1.95407	55.01	0	103.666	111.326
CM2	-2.41264	2.3758	-1.02	0.3099	-7.06913	2.24385
CM3	-					
	6.15102***	1.75059	-3.51	0.0004	-9.58212	-2.71993
CM4	-3.78821**	1.76066	-2.15	0.0314	-7.23904	-0.33737
Scale parameters for dist. Of random parameters						
Constant/BASE	18.8480***	0.48315	39.01	0	17.9011	19.795
CM2	2.10926**	0.85716	2.46	0.0139	0.42925	3.78926
CM3	4.06098***	0.96384	4.21	0	2.17188	5.95007
CM4	3.10758***	0.95516	3.25	0.0011	1.2355	4.97966
Heterogeneity in the means of random parameters						
BASE_C_OV	3.50301***	0.26566	13.19	0	2.98232	4.02369
	-					
BASE_C_E	1.99426***	0.60448	-3.3	0.001	-3.17902	-0.8095
BASE_C_AV	0.0113	0.4023	0.03	0.9776	-0.7772	0.7998
CM2_C_OV	-0.38456	0.47291	-0.81	0.4161	-1.31145	0.54233
CM2_C_E	0.59143	1.1108	0.53	0.5944	-1.5857	2.76856
CM2_C_AV	-0.05849	0.90285	-0.06	0.9483	-1.82804	1.71106
CM3_C_OV	-.98980**	0.40414	-2.45	0.0143	-1.7819	-0.1977
cCM3_C_E	0.85563	0.84376	1.01	0.3106	-0.79811	2.50936
CM3_C_AV	-0.2251	0.53141	-0.42	0.6719	-1.26664	0.81644
CM4_C_OV	-.67609*	0.40324	-1.68	0.0936	-1.46642	0.11424
CM4_C_E	0.3759	0.85393	0.44	0.6598	-1.29778	2.04957
CM4_C_AV	-0.29004	0.49174	-0.59	0.5553	-1.25384	0.67376
Variance parameter given is sigma						
Std.Dev.	6.28234***	0.21635	29.04	0	5.8583	6.70639

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable AVSPD_A

Log likelihood function -840.04648

Estimation based on N = 224, K = 23

Inf.Cr.AIC = 1726.1 AIC/N = 7.706

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	.69978***	0.07265	9.63	0	0.55738	0.84217
TIME	1.04960*	0.588	1.79	0.0743	-0.10285	2.20205
Means for random parameters						
Constant/BASE	105.272***	1.99397	52.8	0	101.364	109.18
CM2	-2.50664	2.13332	-1.17	0.24	-6.68787	1.67459
CM3	-3.63701*	1.97553	-1.84	0.0656	-7.50898	0.23496
CM4	-6.53603***	1.58342	-4.13	0	-9.63947	-3.43259
Scale parameters for dist. Of random parameters						
Constant/BASE	15.4387***	0.3666	42.11	0	14.7201	16.1572
CM2	2.18394**	1.03146	2.12	0.0342	0.16231	4.20557
CM3	1.60196	1.03633	1.55	0.1222	-0.4292	3.63313
CM4	6.19428***	1.11542	5.55	0	4.00811	8.38046
Heterogeneity in the means of random parameters						
BASE_C_OV	3.27150***	0.30016	10.9	0	2.68319	3.8598
BASE_C_E	-1.68047**	0.71219	-2.36	0.0183	-3.07634	-0.28459
BASE_C_AV	-0.2186	0.37464	-0.58	0.5596	-0.95287	0.51567
CM2_C_OV	-0.32148	0.47118	-0.68	0.4951	-1.24497	0.60201
CM2_C_E	0.83045	1.22565	0.68	0.4981	-1.57178	3.23268
CM2_C_AV	-0.1004	0.72492	-0.14	0.8898	-1.52121	1.32041
CM3_C_OV	-0.41452	0.58374	-0.71	0.4776	-1.55864	0.72959
cCM3_C_E	0.48621	1.0868	0.45	0.6546	-1.64388	2.6163
CM3_C_AV	-0.19963	0.67055	-0.3	0.7659	-1.51389	1.11463
CM4_C_OV	-1.04852***	0.35974	-2.91	0.0036	-1.7536	-0.34344
CM4_C_E	0.63737	0.83949	0.76	0.4477	-1.008	2.28273
CM4_C_AV	-0.2012	0.43118	-0.47	0.6408	-1.0463	0.64391
Variance parameter given is sigma						
Std.Dev.	6.53304***	0.20783	31.43	0	6.12571	6.94038

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable AVSPD_T
 Log likelihood function -843.03012
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = 1732.1 AIC/N = 7.732
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	1.21208***	0.06807	17.81	0	1.07865	1.3455
TIME	1.37508**	0.6173	2.23	0.0259	0.16519	2.58497
Means for random parameters						
Constant/BASE	106.004***	2.29101	46.27	0	101.514	110.494
CM2	-1.81385	2.63821	-0.69	0.4917	-6.98464	3.35694
CM3	-3.46596	2.14941	-1.61	0.1068	-7.67873	0.74681
CM4	-5.43325***	1.95639	-2.78	0.0055	-9.26771	-1.5988
Scale parameters for dist. Of random parameters						
Constant/BASE	16.5074***	0.4669	35.36	0	15.5923	17.4225
CM2	2.24741*	1.15937	1.94	0.0526	-0.0249	4.51973
CM3	1.39604	1.08932	1.28	0.2	-0.73899	3.53106
CM4	0.47405	1.02266	0.46	0.643	-1.53033	2.47843
Heterogeneity in the means of random parameters						
BASE_C_OV	2.57196***	0.35135	7.32	0	1.88332	3.26059
BASE_C_E	-0.40384	0.75368	-0.54	0.5921	-1.88103	1.07334
BASE_C_AV	-0.15422	0.4392	-0.35	0.7255	-1.01505	0.7066
CM2_C_OV	-0.3773	0.65535	-0.58	0.5648	-1.66176	0.90716
CM2_C_E	0.45336	1.37285	0.33	0.7412	-2.23738	3.1441
CM2_C_AV	0.11394	0.95202	0.12	0.9047	-1.75198	1.97986
CM3_C_OV	-0.4407	0.64617	-0.68	0.4952	-1.70717	0.82578
cCM3_C_E	0.6736	1.30599	0.52	0.606	-1.88609	3.2333
CM3_C_AV	-0.28054	0.62516	-0.45	0.6536	-1.50583	0.94476
CM4_C_OV	-1.05401***	0.37268	-2.83	0.0047	-1.78446	-0.32356
CM4_C_E	0.81119	0.79683	1.02	0.3087	-0.75056	2.37294
CM4_C_AV	-0.14654	0.47982	-0.31	0.7601	-1.08696	0.79388
Variance parameter given is sigma						
Std.Dev.	6.62241***	0.26286	25.19	0	6.10721	7.13762

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable SDSPD_B
 Log likelihood function -346.48210
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = 739.0 AIC/N = 3.299
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	.02322***	0.00497	4.67	0	0.01348	0.03295
TIME	-.08125**	0.03696	-2.2	0.0279	-0.15369	-0.00882
Means for random parameters						
Constant/BASE	1.69900***	0.11425	14.87	0	1.47506	1.92293
CM2	0.09871	0.14079	0.7	0.4832	-0.17723	0.37465
CM3	1.44503***	0.09896	14.6	0	1.25107	1.63899
CM4	-0.1195	0.12893	-0.93	0.354	-0.3722	0.1332
Scale parameters for dist. Of random parameters						
Constant/BASE	.99094***	0.05129	19.32	0	0.89041	1.09147
CM2	0.03692	0.08999	0.41	0.6816	-0.13945	0.21329
CM3	4.43385***	0.14087	31.48	0	4.15776	4.70995
CM4	.32658***	0.09106	3.59	0.0003	0.1481	0.50505
Heterogeneity in the means of random parameters						
BASE_C_OV	0.0091	0.02584	0.35	0.7249	-0.04156	0.05975
BASE_C_E	0.05292	0.04751	1.11	0.2653	-0.04019	0.14603
BASE_C_AV	-0.02543	0.02646	-0.96	0.3365	-0.07729	0.02642
CM2_C_OV	-0.01747	0.03928	-0.44	0.6565	-0.09447	0.05952
CM2_C_E	-0.00622	0.07561	-0.08	0.9345	-0.15442	0.14198
CM2_C_AV	0.03304	0.04334	0.76	0.4459	-0.0519	0.11798
CM3_C_OV	.66579***	0.02759	24.13	0	0.6117	0.71987
cCM3_C_E	-.43224***	0.05809	-7.44	0	-0.54609	-0.31839
CM3_C_AV	.15469***	0.03573	4.33	0	0.08467	0.22472
CM4_C_OV	0.03879	0.03567	1.09	0.2769	-0.03113	0.10871
CM4_C_E	-0.02303	0.06892	-0.33	0.7383	-0.15811	0.11205
CM4_C_AV	0.0146	0.03555	0.41	0.6813	-0.05507	0.08428
Variance parameter given is sigma						
Std.Dev.	.53129***	0.02401	22.13	0	0.48424	0.57835

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable SDSPD_C
 Log likelihood function -315.62760
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = 677.3 AIC/N = 3.023
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.03165***	0.00837	-3.78	0.0002	-0.04805	-0.01524
TIME	-.11569*	0.06883	-1.68	0.0928	-0.25059	0.01921
Means for random parameters						
Constant/BASE	2.04145***	0.29581	6.9	0	1.46167	2.62124
CM2	-0.10884	0.36877	-0.3	0.7679	-0.83161	0.61393
CM3	.52797*	0.28168	1.87	0.0609	-0.02411	1.08004
CM4	0.44719	0.29673	1.51	0.1318	-0.13439	1.02877
Scale parameters for dist. Of random parameters						
Constant/BASE	.96193***	0.06738	14.28	0	0.82987	1.094
CM2	0.17095	0.13424	1.27	0.2029	-0.09215	0.43405
CM3	.37903***	0.10197	3.72	0.0002	0.17918	0.57888
CM4	.25093**	0.10577	2.37	0.0177	0.04362	0.45823
Heterogeneity in the means of random parameters						
BASE_C_OV	0.05565	0.06794	0.82	0.4128	-0.07751	0.1888
BASE_C_E	0.00694	0.09967	0.07	0.9445	-0.18841	0.20229
BASE_C_AV	-0.01597	0.06722	-0.24	0.8122	-0.14772	0.11578
CM2_C_OV	-0.0022	0.12444	-0.02	0.9859	-0.2461	0.24169
CM2_C_E	-0.03104	0.16037	-0.19	0.8465	-0.34535	0.28327
CM2_C_AV	-0.02221	0.11077	-0.2	0.8411	-0.23931	0.19489
CM3_C_OV	0.03588	0.07488	0.48	0.6319	-0.11089	0.18265
cCM3_C_E	-0.05366	0.12393	-0.43	0.665	-0.29655	0.18923
CM3_C_AV	0.05437	0.09666	0.56	0.5738	-0.13508	0.24382
CM4_C_OV	-0.02078	0.07806	-0.27	0.7901	-0.17378	0.13222
CM4_C_E	-0.00585	0.13686	-0.04	0.9659	-0.27409	0.26239
CM4_C_AV	0.06123	0.07049	0.87	0.385	-0.07693	0.19939
Variance parameter given is sigma						
Std.Dev.	.83823***	0.03426	24.46	0	0.77108	0.90539

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable SDSPD_A

Log likelihood function -256.96582

Estimation based on N = 224, K = 23

Inf.Cr.AIC = 559.9 AIC/N = 2.500

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.02259***	0.00611	-3.7	0.0002	-0.03456	-0.01062
TIME	-0.07635	0.05539	-1.38	0.1681	-0.18492	0.03223
Means for random parameters						
Constant/BASE	1.84149***	0.16426	11.21	0	1.51954	2.16343
CM2	0.02839	0.20028	0.14	0.8873	-0.36416	0.42094
CM3	0.10819	0.16216	0.67	0.5046	-0.20964	0.42603
CM4	0.10109	0.14958	0.68	0.4991	-0.19207	0.39425
Scale parameters for dist. Of random parameters						
Constant/BASE	.48218***	0.0427	11.29	0	0.3985	0.56586
CM2	0.14069	0.09119	1.54	0.1229	-0.03804	0.31943
CM3	.14586*	0.08057	1.81	0.0702	-0.01205	0.30377
CM4	.35843***	0.08978	3.99	0.0001	0.18247	0.5344
Heterogeneity in the means of random parameters						
BASE_C_OV	-0.00609	0.03642	-0.17	0.8673	-0.07747	0.0653
BASE_C_E	-0.00833	0.06491	-0.13	0.8979	-0.13554	0.11889
BASE_C_AV	-0.00059	0.03869	-0.02	0.9878	-0.07641	0.07523
CM2_C_OV	-0.04047	0.06597	-0.61	0.5395	-0.16977	0.08882
CM2_C_E	0.01997	0.09473	0.21	0.833	-0.16568	0.20563
CM2_C_AV	0.01904	0.06388	0.3	0.7657	-0.10617	0.14424
CM3_C_OV	-0.03618	0.03783	-0.96	0.3389	-0.11033	0.03797
cCM3_C_E	0.04935	0.08938	0.55	0.5809	-0.12584	0.22454
CM3_C_AV	0.00456	0.04262	0.11	0.9148	-0.07898	0.0881
CM4_C_OV	0.0258	0.0455	0.57	0.5707	-0.06338	0.11499
CM4_C_E	-0.0059	0.08359	-0.07	0.9437	-0.16974	0.15794
CM4_C_AV	0.04078	0.05345	0.76	0.4455	-0.06398	0.14554
Variance parameter given is sigma						
Std.Dev.	.62882***	0.02698	23.31	0	0.57594	0.68169

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable SDSPD_T
 Log likelihood function -519.51735
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = 1085.0 AIC/N = 4.844
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.08318***	0.0156	-5.33	0	-0.11375	-0.05261
TIME	-0.11432	0.14578	-0.78	0.4329	-0.40004	0.1714
Means for random parameters						
Constant/BASE	5.30777***	0.55779	9.52	0	4.21452	6.40102
CM2	-0.03793	0.50411	-0.08	0.94	-1.02596	0.9501
CM3	1.49779***	0.40012	3.74	0.0002	0.71356	2.28202
CM4	-0.04359	0.56249	-0.08	0.9382	-1.14604	1.05887
Scale parameters for dist. Of random parameters						
Constant/BASE	3.80310***	0.13109	29.01	0	3.54618	4.06003
CM2	0.0059	0.28244	0.02	0.9833	-0.54767	0.55946
CM3	4.06506***	0.19069	21.32	0	3.6913	4.43881
CM4	0.23323	0.29961	0.78	0.4363	-0.354	0.82046
Heterogeneity in the means of random parameters						
BASE_C_OV	.36247***	0.10084	3.59	0.0003	0.16483	0.56011
BASE_C_E	-0.09087	0.16234	-0.56	0.5756	-0.40905	0.2273
BASE_C_AV	-0.12203	0.08356	-1.46	0.1442	-0.28581	0.04174
CM2_C_OV	-0.00835	0.18629	-0.04	0.9643	-0.37347	0.35677
CM2_C_E	-0.17908	0.28714	-0.62	0.5328	-0.74186	0.3837
CM2_C_AV	0.08631	0.14288	0.6	0.5458	-0.19373	0.36636
CM3_C_OV	0.16465	0.11664	1.41	0.1581	-0.06397	0.39326
cCM3_C_E	-0.14704	0.20022	-0.73	0.4627	-0.53946	0.24538
CM3_C_AV	-0.02629	0.12015	-0.22	0.8268	-0.26178	0.20919
CM4_C_OV	-0.00884	0.14295	-0.06	0.9507	-0.28902	0.27133
CM4_C_E	-0.0481	0.31964	-0.15	0.8804	-0.67459	0.57838
CM4_C_AV	-0.01953	0.17209	-0.11	0.9097	-0.35682	0.31777
Variance parameter given is sigma						
Std.Dev.	1.54506***	0.07165	21.56	0	1.40463	1.68549

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable AVTRJ_B
 Log likelihood function 150.70548
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 301.41096
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -255.4 AIC/N = -1.140
 Unbalanced panel has 56 individuals
 LINEAR regression model

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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00269***	0.00086	-3.12	0.0018	-0.00438	-0.001
TIME	.46906D-04	0.00554	0.01	0.9932	-.10808D-01	.10902D-01
Means for random parameters						
Constant/BASE	1.56716***	0.01973	79.42	0	1.52848	1.60584
CM2	-.05513***	0.0181	-3.05	0.0023	-0.09061	-0.01966
CM3	-.05788***	0.01854	-3.12	0.0018	-0.09423	-0.02154
CM4	-0.01328	0.02001	-0.66	0.507	-0.0525	0.02594
Scale parameters for dist. Of random parameters						
Constant/BASE	.14044***	0.00615	22.84	0	0.12838	0.15249
CM2	.02545**	0.01214	2.1	0.036	0.00166	0.04924
CM3	.05939***	0.01213	4.89	0	0.03561	0.08317
CM4	0.00291	0.01286	0.23	0.8212	-0.02229	0.0281
Heterogeneity in the means of random parameters						
BASE_C_OV	0.00055	0.00313	0.18	0.86	-0.00559	0.0067
BASE_C_E	-.01217**	0.00507	-2.4	0.0165	-0.02212	-0.00223
BASE_C_AV	.01319***	0.00447	2.95	0.0032	0.00443	0.02195
CM2_C_OV	-0.00527	0.00478	-1.1	0.2697	-0.01463	0.00409
CM2_C_E	0.01295	0.0097	1.34	0.1818	-0.00606	0.03196
CM2_C_AV	-0.00399	0.00648	-0.62	0.5376	-0.01669	0.0087
CM3_C_OV	-.01076**	0.00432	-2.49	0.0127	-0.01922	-0.0023
cCM3_C_E	.01556*	0.00815	1.91	0.0563	-0.00042	0.03154
CM3_C_AV	0.00614	0.00653	0.94	0.3469	-0.00666	0.01895
CM4_C_OV	-0.00516	0.00538	-0.96	0.337	-0.0157	0.00537
CM4_C_E	.01499*	0.00783	1.91	0.0556	-0.00036	0.03034
CM4_C_AV	-0.0072	0.00779	-0.92	0.3556	-0.02247	0.00807
Variance parameter given is sigma						
Std.Dev.	.08718***	0.00417	20.9	0	0.07901	0.09536

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Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

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 Random Coefficients LinearRg Model
 Dependent variable AVTRJ_C
 Log likelihood function 194.72820
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 389.45641
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -343.5 AIC/N = -1.533
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00575***	0.00067	-8.53	0	-0.00707	-0.00443
TIME	.01095***	0.00394	2.78	0.0054	0.00323	0.01866
Means for random parameters						
Constant/BASE	1.53024***	0.01489	102.77	0	1.50106	1.55943
CM2	-.03314**	0.01365	-2.43	0.0152	-0.0599	-0.00638
CM3	-0.01093	0.01368	-0.8	0.4243	-0.03775	0.01588
CM4	-.04815***	0.01378	-3.49	0.0005	-0.07517	-0.02114
Scale parameters for dist. Of random parameters						
Constant/BASE	.12071***	0.00494	24.45	0	0.11103	0.13038
CM2	.03981***	0.00974	4.09	0	0.02071	0.05891
CM3	.02609***	0.00946	2.76	0.0058	0.00755	0.04463
CM4	.05342***	0.01028	5.2	0	0.03327	0.07357
Heterogeneity in the means of random parameters						
BASE_C_OV	-.00797***	0.00291	-2.74	0.0062	-0.01367	-0.00227
BASE_C_E	-0.00261	0.00451	-0.58	0.563	-0.01144	0.00623
BASE_C_AV	.00740**	0.00312	2.37	0.0178	0.00128	0.01351
CM2_C_OV	0.00259	0.00442	0.59	0.5579	-0.00607	0.01125
CM2_C_E	-0.00906	0.00603	-1.5	0.1331	-0.02089	0.00276
CM2_C_AV	-0.00075	0.005	-0.15	0.8805	-0.01055	0.00905
CM3_C_OV	-0.00282	0.004	-0.7	0.4815	-0.01065	0.00502
cCM3_C_E	0.00532	0.00749	0.71	0.4778	-0.00936	0.02
CM3_C_AV	.00812*	0.0046	1.77	0.0774	-0.00089	0.01712
CM4_C_OV	0.00549	0.00417	1.32	0.1881	-0.00269	0.01367
CM4_C_E	0.00545	0.00657	0.83	0.4071	-0.00743	0.01832
CM4_C_AV	0.00018	0.00425	0.04	0.9669	-0.00816	0.00851
Variance parameter given is sigma						
Std.Dev.	.06561***	0.00321	20.45	0	0.05933	0.0719

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable AVTRJ_A
 Log likelihood function 141.27969
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 282.55937
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -236.6 AIC/N = -1.056
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00549***	0.0008	-6.85	0	-0.00706	-0.00392
TIME	.02132***	0.00509	4.19	0	0.01135	0.0313
Means for random parameters						
Constant/BASE	1.34768***	0.016	84.24	0	1.31633	1.37904
CM2	-0.01521	0.0157	-0.97	0.3325	-0.04599	0.01556
CM3	-0.01113	0.01503	-0.74	0.4587	-0.04059	0.01832
CM4	.10132***	0.01474	6.88	0	0.07244	0.1302
Scale parameters for dist. Of random parameters						
Constant/BASE	.13441***	0.00581	23.14	0	0.12302	0.14579
CM2	.07804***	0.01079	7.24	0	0.0569	0.09918
CM3	0.01621	0.01139	1.42	0.1548	-0.00612	0.03854
CM4	.10387***	0.01125	9.24	0	0.08183	0.12591
Heterogeneity in the means of random parameters						
BASE_C_OV	-.00628**	0.00275	-2.28	0.0226	-0.01168	-0.00088
BASE_C_E	-.00980*	0.00514	-1.9	0.0569	-0.01988	0.00029
BASE_C_AV	0.00106	0.00366	0.29	0.773	-0.00612	0.00823
CM2_C_OV	-0.00191	0.00389	-0.49	0.6225	-0.00953	0.0057
CM2_C_E	0.00081	0.00819	0.1	0.9215	-0.01524	0.01685
CM2_C_AV	0.0022	0.00548	0.4	0.6883	-0.00855	0.01295
CM3_C_OV	-0.0052	0.00389	-1.34	0.1814	-0.01282	0.00243
cCM3_C_E	.01616**	0.00823	1.96	0.0495	0.00003	0.03229
CM3_C_AV	0.00407	0.00507	0.8	0.4217	-0.00586	0.014
CM4_C_OV	.00870*	0.00451	1.93	0.0538	-0.00014	0.01755
CM4_C_E	.01289*	0.00701	1.84	0.0661	-0.00086	0.02663
CM4_C_AV	-0.00674	0.00546	-1.23	0.2175	-0.01744	0.00397
Variance parameter given is sigma						
Std.Dev.	.07887***	0.0038	20.73	0	0.07141	0.08633

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable AVTRJ_T
 Log likelihood function 204.60194
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 409.20388
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -363.2 AIC/N = -1.621
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00439***	0.00065	-6.77	0	-0.00566	-0.00312
TIME	0.00685	0.00436	1.57	0.1161	-0.0017	0.0154
Means for random parameters						
Constant/BASE	1.50404***	0.01591	94.52	0	1.47285	1.53523
CM2	-.02778**	0.01371	-2.03	0.0427	-0.05465	-0.00091
CM3	-.03483**	0.01429	-2.44	0.0148	-0.06284	-0.00682
CM4	0.00756	0.01419	0.53	0.594	-0.02024	0.03537
Scale parameters for dist. Of random parameters						
Constant/BASE	.12921***	0.00452	28.61	0	0.12036	0.13806
CM2	0.00324	0.00942	0.34	0.7305	-0.01521	0.0217
CM3	.03339***	0.0093	3.59	0.0003	0.01517	0.05162
CM4	.02477***	0.00921	2.69	0.0071	0.00672	0.04281
Heterogeneity in the means of random parameters						
BASE_C_OV	-.17745D-04	0.00234	-0.01	0.9939	-.45992D-02	.45637D-02
BASE_C_E	-.01581***	0.00464	-3.4	0.0007	-0.02492	-0.00671
BASE_C_AV	.00611**	0.0029	2.11	0.035	0.00043	0.01179
CM2_C_OV	-0.00448	0.00358	-1.25	0.2107	-0.0115	0.00254
CM2_C_E	0.01126	0.0072	1.56	0.1177	-0.00285	0.02536
CM2_C_AV	-0.00171	0.00565	-0.3	0.7623	-0.01279	0.00937
CM3_C_OV	-.00610*	0.00366	-1.66	0.0961	-0.01328	0.00109
cCM3_C_E	.02131**	0.00882	2.42	0.0157	0.00402	0.0386
CM3_C_AV	0.00263	0.00547	0.48	0.6313	-0.0081	0.01335
CM4_C_OV	0.00081	0.00336	0.24	0.8104	-0.00577	0.00738
CM4_C_E	.01789***	0.00552	3.24	0.0012	0.00707	0.0287
CM4_C_AV	-.00711*	0.00389	-1.83	0.0678	-0.01474	0.00052
Variance parameter given is sigma						
Std.Dev.	.06548***	0.00329	19.89	0	0.05903	0.07194

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 Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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 Random Coefficients LinearRg Model
 Dependent variable SDTRJ_B
 Log likelihood function 437.89253
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 875.78506
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -829.8 AIC/N = -3.704
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00072**	0.0003	-2.42	0.0154	-0.0013	-0.00014
TIME	0.00309	0.00215	1.44	0.1509	-0.00113	0.0073
Means for random parameters						
Constant/BASE	.09295***	0.00762	12.2	0	0.07801	0.10789
CM2	0.00426	0.00574	0.74	0.458	-0.007	0.01552
CM3	.01316**	0.00656	2	0.045	0.00029	0.02603
CM4	-0.00114	0.00712	-0.16	0.8728	-0.0151	0.01282
Scale parameters for dist. Of random parameters						
Constant/BASE	.02052***	0.00187	11	0	0.01686	0.02417
CM2	0.00047	0.00396	0.12	0.9051	-0.00728	0.00823
CM3	.01395***	0.00396	3.52	0.0004	0.00618	0.02171
CM4	0.0007	0.00474	0.15	0.8824	-0.00858	0.00999
Heterogeneity in the means of random parameters						
BASE_C_OV	.00267***	0.00101	2.64	0.0084	0.00068	0.00466
BASE_C_E	-0.00057	0.00208	-0.28	0.7821	-0.00464	0.00349
BASE_C_AV	-0.00139	0.00154	-0.9	0.3676	-0.00442	0.00164
CM2_C_OV	-.00419**	0.00169	-2.48	0.0132	-0.00751	-0.00088
CM2_C_E	0.00478	0.00305	1.57	0.1173	-0.0012	0.01076
CM2_C_AV	0.00307	0.00192	1.6	0.1101	-0.0007	0.00685
CM3_C_OV	-0.00199	0.00174	-1.14	0.2531	-0.00541	0.00142
cCM3_C_E	0.00345	0.00318	1.08	0.2787	-0.00279	0.00969
CM3_C_AV	-0.00201	0.00248	-0.81	0.4184	-0.00688	0.00286
CM4_C_OV	-.00286*	0.00167	-1.71	0.0878	-0.00613	0.00042
CM4_C_E	0.00299	0.00366	0.82	0.4147	-0.00419	0.01017
CM4_C_AV	0.0022	0.00223	0.99	0.3222	-0.00216	0.00656
Variance parameter given is sigma						
Std.Dev.	.02948***	0.00152	19.43	0	0.02651	0.03246

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable SDTRJ_C
 Log likelihood function 413.21022
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 826.42043
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -780.4 AIC/N = -3.484
 Unbalanced panel has 56 individuals
 LINEAR regression model

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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00175***	0.00027	-6.59	0	-0.00227	-0.00123
TIME	-0.00183	0.00196	-0.94	0.3496	-0.00568	0.00201
Means for random parameters						
Constant/BASE	.17498***	0.00624	28.03	0	0.16275	0.18722
CM2	-0.00198	0.00545	-0.36	0.716	-0.01266	0.0087
CM3	.00896*	0.00506	1.77	0.0769	-0.00097	0.01888
CM4	.01179**	0.00533	2.21	0.027	0.00134	0.02224
Scale parameters for dist. Of random parameters						
Constant/BASE	.03629***	0.00185	19.57	0	0.03266	0.03993
CM2	.01785***	0.00382	4.68	0	0.01037	0.02533
CM3	.02245***	0.00367	6.11	0	0.01526	0.02965
CM4	.01281***	0.0037	3.46	0.0005	0.00555	0.02006
Heterogeneity in the means of random parameters						
BASE_C_OV	.00252**	0.00108	2.34	0.0192	0.00041	0.00463
BASE_C_E	-.70989D-05	0.00183	0	0.9969	-.35872D-02	.35730D-02
BASE_C_AV	-0.00083	0.00123	-0.67	0.5021	-0.00324	0.00159
CM2_C_OV	-0.00192	0.0015	-1.28	0.2006	-0.00486	0.00102
CM2_C_E	.00553**	0.00256	2.16	0.0311	0.0005	0.01055
CM2_C_AV	0.00026	0.00189	0.14	0.8893	-0.00345	0.00397
CM3_C_OV	0.00034	0.00161	0.21	0.832	-0.00281	0.00349
cCM3_C_E	0.00112	0.00245	0.45	0.6495	-0.0037	0.00593
CM3_C_AV	0.00041	0.00177	0.23	0.8159	-0.00306	0.00389
CM4_C_OV	-.00238*	0.00144	-1.66	0.0972	-0.0052	0.00043
CM4_C_E	.00485*	0.00284	1.71	0.0878	-0.00072	0.01042
CM4_C_AV	-0.00044	0.0018	-0.24	0.8085	-0.00397	0.0031
Variance parameter given is sigma						
Std.Dev.	.02593***	0.0013	19.94	0	0.02338	0.02848

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Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

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 Random Coefficients LinearRg Model
 Dependent variable SDTRJ_A
 Log likelihood function 365.29127
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 730.58254
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -684.6 AIC/N = -3.056
 Unbalanced panel has 56 individuals
 LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00097**	0.00043	-2.26	0.0236	-0.00181	-0.00013
TIME	-0.00074	0.00262	-0.28	0.777	-0.00587	0.00439
Means for random parameters						
Constant/BASE	.12760***	0.00981	13.01	0	0.10838	0.14682
CM2	0.00082	0.00934	0.09	0.9301	-0.01749	0.01913
CM3	-0.00141	0.00853	-0.17	0.8683	-0.01813	0.0153
CM4	.02238***	0.00858	2.61	0.0091	0.00556	0.0392
Scale parameters for dist. Of random parameters						
Constant/BASE	.02766***	0.00295	9.37	0	0.02188	0.03345
CM2	0.0043	0.00539	0.8	0.4252	-0.00626	0.01486
CM3	0.00288	0.00571	0.51	0.6133	-0.0083	0.01407
CM4	.02696***	0.0054	4.99	0	0.01638	0.03754
Heterogeneity in the means of random parameters						
BASE_C_OV	0.00213	0.00147	1.45	0.1462	-0.00074	0.00501
BASE_C_E	-0.00217	0.00382	-0.57	0.5705	-0.00965	0.00532
BASE_C_AV	-0.00081	0.00218	-0.37	0.7108	-0.00508	0.00346
CM2_C_OV	0.00213	0.00233	0.91	0.361	-0.00244	0.00669
CM2_C_E	0.00293	0.0058	0.5	0.6136	-0.00845	0.01431
CM2_C_AV	0.00107	0.00329	0.33	0.7448	-0.00538	0.00752
CM3_C_OV	-.00388*	0.00202	-1.92	0.0553	-0.00784	0.00009
cCM3_C_E	-.83758D-04	0.00588	-0.01	0.9886	-.11605D-01	.11437D-01
CM3_C_AV	0.00351	0.00294	1.2	0.2319	-0.00225	0.00927
CM4_C_OV	-0.00056	0.00266	-0.21	0.8321	-0.00577	0.00465
CM4_C_E	-0.00049	0.00471	-0.1	0.9179	-0.00971	0.00874
CM4_C_AV	0.00151	0.00359	0.42	0.6737	-0.00552	0.00854
Variance parameter given is sigma						
Std.Dev.	.03981***	0.00165	24.06	0	0.03657	0.04306

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 Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

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Random Coefficients LinearRg Model

Dependent variable SDTRJ_T
 Log likelihood function 420.61934
 Restricted log likelihood .00000
 Chi squared [16 d.f.] 841.23868
 Significance level .00000
 Estimation based on N = 224, K = 23
 Inf.Cr.AIC = -795.2 AIC/N = -3.550
 Unbalanced panel has 56 individuals
 LINEAR regression model

	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-0.00033	0.00025	-1.3	0.1949	-0.00083	0.00017
TIME	.00635***	0.00176	3.61	0.0003	0.0029	0.00979
Means for random parameters						
Constant/BASE	.16952***	0.00521	32.55	0	0.15931	0.17973
CM2	-0.00598	0.00468	-1.28	0.2014	-0.01515	0.00319
CM3	-0.00379	0.00517	-0.73	0.464	-0.01393	0.00635
CM4	-.00913*	0.00473	-1.93	0.0534	-0.0184	0.00013
Scale parameters for dist. Of random parameters						
Constant/BASE	.03610***	0.00193	18.71	0	0.03232	0.03988
CM2	.02692***	0.00347	7.75	0	0.02011	0.03372
CM3	.01458***	0.00337	4.32	0	0.00796	0.02119
CM4	0.00424	0.00367	1.16	0.2475	-0.00295	0.01143
Heterogeneity in the means of random parameters						
BASE_C_OV	.00316***	0.00108	2.92	0.0035	0.00104	0.00528
BASE_C_E	0.0012	0.00167	0.72	0.4706	-0.00207	0.00448
BASE_C_AV	-0.0003	0.00123	-0.24	0.8098	-0.00272	0.00212
CM2_C_OV	-0.0003	0.00118	-0.25	0.7994	-0.00262	0.00202
CM2_C_E	0.00138	0.00236	0.59	0.5572	-0.00324	0.00601
CM2_C_AV	0.00028	0.00166	0.17	0.8655	-0.00296	0.00352
CM3_C_OV	-0.00021	0.00149	-0.14	0.8897	-0.00312	0.00271
cCM3_C_E	-0.00118	0.00248	-0.47	0.6348	-0.00605	0.00369
CM3_C_AV	0.00088	0.00183	0.48	0.6289	-0.0027	0.00447
CM4_C_OV	-0.00155	0.00197	-0.79	0.4313	-0.00541	0.00231
CM4_C_E	-0.00025	0.00326	-0.08	0.938	-0.00665	0.00614
CM4_C_AV	0.00055	0.00218	0.25	0.8006	-0.00372	0.00482
Variance parameter given is sigma						
Std.Dev.	.02514***	0.00108	23.21	0	0.02301	0.02726

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 Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable NC_B

Log likelihood function 310.15881

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -574.3 AIC/N = -2.564

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-0.00037	0.0004	-0.94	0.3496	-0.00116	0.00041
TIME	.02211***	0.00282	7.84	0	0.01659	0.02764
Means for random parameters						
Constant/BASE	.09121***	0.00902	10.11	0	0.07352	0.10889
CM2	-0.00096	0.00781	-0.12	0.9024	-0.01627	0.01435
CM3	-0.01059	0.00934	-1.13	0.2567	-0.0289	0.00771
CM4	0.01235	0.00821	1.51	0.1323	-0.00373	0.02843
Scale parameters for dist. Of random parameters						
Constant/BASE	.04745***	0.00291	16.29	0	0.04174	0.05316
CM2	.06431***	0.00566	11.37	0	0.05322	0.07539
CM3	0.00814	0.00579	1.41	0.1596	-0.00321	0.01949
CM4	.03062***	0.00584	5.24	0	0.01916	0.04207
Heterogeneity in the means of random parameters						
BASE_C_OV	-.00598***	0.0015	-3.99	0.0001	-0.00891	-0.00304
BASE_C_E	-0.00039	0.00308	-0.13	0.8982	-0.00643	0.00564
BASE_C_AV	0.00289	0.00194	1.49	0.1362	-0.00091	0.00668
CM2_C_OV	.00479**	0.00215	2.23	0.026	0.00057	0.009
CM2_C_E	-0.00383	0.00427	-0.9	0.3697	-0.01221	0.00454
CM2_C_AV	-.00648***	0.00242	-2.68	0.0074	-0.01123	-0.00174
CM3_C_OV	0.00119	0.00223	0.53	0.5928	-0.00318	0.00556
cCM3_C_E	-0.00218	0.00482	-0.45	0.6511	-0.01163	0.00727
CM3_C_AV	0.00029	0.00285	0.1	0.9196	-0.00529	0.00587
CM4_C_OV	0.00231	0.00238	0.97	0.3307	-0.00235	0.00697
CM4_C_E	-0.00083	0.00381	-0.22	0.8268	-0.00829	0.00663
CM4_C_AV	-.00443*	0.00264	-1.68	0.0929	-0.00959	0.00074
Variance parameter given is sigma						
Std.Dev.	.04048***	0.00202	20.03	0	0.03652	0.04444

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable NC_C

Log likelihood function 475.58496

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -905.2 AIC/N = -4.041

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	0.0001	0.00019	0.53	0.5952	-0.00027	0.00047
TIME	.01776***	0.00126	14.05	0	0.01528	0.02023
Means for random parameters						
Constant/BASE	.04027***	0.00441	9.13	0	0.03163	0.04892
CM2	0.00611	0.00407	1.5	0.133	-0.00186	0.01409
CM3	-0.00196	0.00394	-0.5	0.6195	-0.00967	0.00576
CM4	-0.00269	0.00381	-0.71	0.4805	-0.01017	0.00478
Scale parameters for dist. Of random parameters						
Constant/BASE	.01948***	0.00141	13.84	0	0.01672	0.02224
CM2	.02350***	0.00262	8.96	0	0.01836	0.02864
CM3	.01335***	0.0026	5.14	0	0.00826	0.01845
CM4	.02383***	0.00244	9.75	0	0.01904	0.02862
Heterogeneity in the means of random parameters						
BASE_C_OV	-.00219***	0.00074	-2.96	0.0031	-0.00365	-0.00074
BASE_C_E	-0.00063	0.00137	-0.46	0.6464	-0.00332	0.00206
BASE_C_AV	-0.00073	0.00093	-0.78	0.4361	-0.00256	0.0011
CM2_C_OV	-.72788D-04	0.00099	-0.07	0.9414	-.20150D-02	.18695D-02
CM2_C_E	-0.00056	0.00191	-0.3	0.767	-0.0043	0.00317
CM2_C_AV	0.00053	0.00128	0.42	0.677	-0.00197	0.00303
CM3_C_OV	-0.00026	0.00113	-0.23	0.8185	-0.00248	0.00196
cCM3_C_E	.00346*	0.00183	1.89	0.059	-0.00013	0.00706
CM3_C_AV	-0.00078	0.00138	-0.57	0.5712	-0.0035	0.00193
CM4_C_OV	.00297***	0.00094	3.16	0.0016	0.00112	0.00481
CM4_C_E	-0.00275	0.00197	-1.4	0.1618	-0.0066	0.0011
CM4_C_AV	-0.00089	0.0012	-0.75	0.4558	-0.00323	0.00145
Variance parameter given is sigma						
Std.Dev.	.01881***	0.00086	21.76	0	0.01712	0.02051

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable NC_A

Log likelihood function 423.20688

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -800.4 AIC/N = -3.573

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-0.00017	0.00032	-0.53	0.5989	-0.00081	0.00046
TIME	.01836***	0.00244	7.53	0	0.01359	0.02314
Means for random parameters						
Constant/BASE	.03560***	0.00821	4.34	0	0.01951	0.0517
CM2	0.00585	0.00727	0.81	0.4203	-0.00838	0.02009
CM3	0.00087	0.00548	0.16	0.8737	-0.00986	0.0116
CM4	0.00179	0.00618	0.29	0.7716	-0.01031	0.0139
Scale parameters for dist. Of random parameters						
Constant/BASE	.02009***	0.00212	9.45	0	0.01592	0.02425
CM2	0.00088	0.00478	0.18	0.8533	-0.00848	0.01024
CM3	.01230***	0.00432	2.85	0.0044	0.00383	0.02076
CM4	.02102***	0.00442	4.75	0	0.01236	0.02969
Heterogeneity in the means of random parameters						
BASE_C_OV	-0.00039	0.00131	-0.3	0.7637	-0.00296	0.00217
BASE_C_E	-0.00271	0.00245	-1.1	0.2705	-0.00752	0.00211
BASE_C_AV	-0.00066	0.00208	-0.32	0.75	-0.00475	0.00342
CM2_C_OV	-0.00172	0.00231	-0.75	0.4553	-0.00625	0.0028
CM2_C_E	0.00061	0.00415	0.15	0.8836	-0.00753	0.00874
CM2_C_AV	0.0009	0.00364	0.25	0.8043	-0.00623	0.00803
CM3_C_OV	-0.00088	0.0017	-0.52	0.6043	-0.0042	0.00245
cCM3_C_E	0.00351	0.0029	1.21	0.2254	-0.00217	0.00919
CM3_C_AV	-0.00053	0.00309	-0.17	0.8632	-0.00658	0.00552
CM4_C_OV	-0.00026	0.00181	-0.14	0.8866	-0.00381	0.00329
CM4_C_E	0.00131	0.00323	0.4	0.6856	-0.00502	0.00764
CM4_C_AV	-0.00071	0.00224	-0.32	0.75	-0.0051	0.00367
Variance parameter given is sigma						
Std.Dev.	.03019***	0.00139	21.7	0	0.02746	0.03291

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable NC_T

Log likelihood function 411.21491

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -776.4 AIC/N = -3.466

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00055**	0.00024	-2.32	0.0201	-0.00102	-0.00009
TIME	.02283***	0.00167	13.7	0	0.01957	0.0261
Means for random parameters						
Constant/BASE	.06021***	0.005	12.04	0	0.05041	0.07001
CM2	0.00071	0.00464	0.15	0.8781	-0.00839	0.00982
CM3	-.01050**	0.00459	-2.29	0.0221	-0.01949	-0.00151
CM4	.70302D-05	0.0043	0	0.9987	-.84227D-02	.84367D-02
Scale parameters for dist. Of random parameters						
Constant/BASE	.03232***	0.00175	18.47	0	0.02889	0.03575
CM2	.03635***	0.00355	10.23	0	0.02939	0.04332
CM3	.01716***	0.00323	5.31	0	0.01083	0.02349
CM4	.02680***	0.0032	8.36	0	0.02052	0.03308
Heterogeneity in the means of random parameters						
BASE_C_OV	-.00325***	0.00098	-3.31	0.0009	-0.00517	-0.00132
BASE_C_E	-.32907D-04	0.00182	-0.02	0.9855	-.35938D-02	.35280D-02
BASE_C_AV	0.00141	0.00109	1.29	0.1965	-0.00073	0.00356
CM2_C_OV	0.00158	0.00137	1.15	0.2493	-0.00111	0.00426
CM2_C_E	0.00062	0.00254	0.24	0.8079	-0.00435	0.00559
CM2_C_AV	-.00336**	0.00154	-2.19	0.0288	-0.00638	-0.00035
CM3_C_OV	0.00038	0.00136	0.28	0.7779	-0.00228	0.00305
cCM3_C_E	0.00123	0.00267	0.46	0.6452	-0.00401	0.00647
CM3_C_AV	-0.00242	0.00169	-1.43	0.1528	-0.00574	0.0009
CM4_C_OV	0.00165	0.0014	1.18	0.2394	-0.0011	0.0044
CM4_C_E	0.00028	0.0024	0.11	0.9087	-0.00442	0.00497
CM4_C_AV	-.00317**	0.00138	-2.29	0.0221	-0.00588	-0.00046
Variance parameter given is sigma						
Std.Dev.	.02313***	0.00113	20.55	0	0.02093	0.02534

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable LV_B

Log likelihood function 428.81611

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -811.6 AIC/N = -3.623

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-0.00031	0.00028	-1.12	0.261	-0.00085	0.00023
TIME	0.00192	0.00251	0.77	0.4427	-0.00299	0.00684
Means for random parameters						
Constant/BASE	0.00766	0.00938	0.82	0.414	-0.01072	0.02605
CM2	-0.0045	0.00984	-0.46	0.6473	-0.02379	0.01478
CM3	.01912***	0.00724	2.64	0.0082	0.00493	0.0333
CM4	-0.00184	0.01024	-0.18	0.8571	-0.02192	0.01823
Scale parameters for dist. Of random parameters						
Constant/BASE	.01416***	0.00184	7.72	0	0.01057	0.01776
CM2	0.00125	0.00466	0.27	0.7877	-0.00787	0.01038
CM3	.08001***	0.00341	23.46	0	0.07333	0.0867
CM4	0.00441	0.00392	1.12	0.2616	-0.00329	0.0121
Heterogeneity in the means of random parameters						
BASE_C_OV	0.00097	0.00219	0.44	0.6571	-0.00332	0.00526
BASE_C_E	-0.00151	0.00366	-0.41	0.6795	-0.00868	0.00566
BASE_C_AV	-0.00246	0.00223	-1.1	0.27	-0.00682	0.00191
CM2_C_OV	-0.00053	0.00387	-0.14	0.8909	-0.00813	0.00706
CM2_C_E	0.0004	0.0061	0.07	0.9476	-0.01155	0.01235
CM2_C_AV	0.00105	0.00446	0.24	0.814	-0.00769	0.00979
CM3_C_OV	0.00275	0.00245	1.12	0.2618	-0.00205	0.00755
cCM3_C_E	-.00798*	0.00415	-1.92	0.0547	-0.01612	0.00016
CM3_C_AV	-.00573**	0.00248	-2.31	0.0207	-0.01058	-0.00088
CM4_C_OV	-.68942D-04	0.00429	-0.02	0.9872	-.84827D-02	.83448D-02
CM4_C_E	-0.00126	0.00575	-0.22	0.8272	-0.01253	0.01002
CM4_C_AV	0.00182	0.0039	0.47	0.6408	-0.00582	0.00945
Variance parameter given is sigma						
Std.Dev.	.02675***	0.00097	27.57	0	0.02485	0.02865

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable LV_C

Log likelihood function 402.70755

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -759.4 AIC/N = -3.390

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	-.00124***	0.00028	-4.45	0	-0.00179	-0.0007
TIME	-0.00062	0.00272	-0.23	0.8186	-0.00594	0.0047
Means for random parameters						
Constant/BASE	.02585***	0.00873	2.96	0.0031	0.00875	0.04296
CM2	0.00527	0.00826	0.64	0.5241	-0.01093	0.02146
CM3	0.00286	0.00826	0.35	0.7293	-0.01333	0.01905
CM4	0.00906	0.00616	1.47	0.1413	-0.00301	0.02112
Scale parameters for dist. Of random parameters						
Constant/BASE	.04937***	0.00177	27.87	0	0.0459	0.05284
CM2	0.00146	0.00431	0.34	0.7341	-0.00698	0.0099
CM3	.01127***	0.00423	2.67	0.0077	0.00298	0.01955
CM4	.01947***	0.004	4.87	0	0.01162	0.02731
Heterogeneity in the means of random parameters						
BASE_C_OV	.00363***	0.00115	3.17	0.0015	0.00139	0.00588
BASE_C_E	-.00780***	0.0024	-3.25	0.0012	-0.01251	-0.0031
BASE_C_AV	-0.00222	0.00157	-1.41	0.1576	-0.00531	0.00086
CM2_C_OV	-0.00161	0.00221	-0.73	0.4656	-0.00594	0.00272
CM2_C_E	.00622*	0.00363	1.71	0.0868	-0.0009	0.01333
CM2_C_AV	0.00033	0.00254	0.13	0.8965	-0.00464	0.0053
CM3_C_OV	-0.00174	0.00191	-0.91	0.3608	-0.00548	0.00199
cCM3_C_E	0.00193	0.00409	0.47	0.6373	-0.00608	0.00994
CM3_C_AV	-0.00079	0.00287	-0.28	0.7823	-0.00642	0.00484
CM4_C_OV	-.00355**	0.00173	-2.05	0.0402	-0.00694	-0.00016
CM4_C_E	.00592**	0.00295	2.01	0.0446	0.00014	0.01169
CM4_C_AV	0.00226	0.0023	0.98	0.326	-0.00224	0.00676
Variance parameter given is sigma						
Std.Dev.	.02922***	0.00124	23.57	0	0.02679	0.03165

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable LV_A

Log likelihood function 296.94924

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -547.9 AIC/N = -2.446

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	.00142***	0.00047	3.03	0.0024	0.0005	0.00234
TIME	-0.00658	0.00422	-1.56	0.1193	-0.01485	0.0017
Means for random parameters						
Constant/BASE	.05377***	0.01395	3.86	0.0001	0.02644	0.08111
CM2	0.0082	0.01094	0.75	0.4535	-0.01324	0.02963
CM3	0.00471	0.01137	0.41	0.6787	-0.01758	0.027
CM4	-0.01529	0.01358	-1.13	0.2603	-0.04191	0.01133
Scale parameters for dist. Of random parameters						
Constant/BASE	.04496***	0.00356	12.63	0	0.03798	0.05194
CM2	.06815***	0.00579	11.77	0	0.0568	0.0795
CM3	.02045***	0.00609	3.36	0.0008	0.00852	0.03238
CM4	0.00375	0.0091	0.41	0.68	-0.01408	0.02158
Heterogeneity in the means of random parameters						
BASE_C_OV	.00802***	0.00223	3.59	0.0003	0.00364	0.0124
BASE_C_E	-0.00568	0.00478	-1.19	0.2348	-0.01506	0.00369
BASE_C_AV	-0.00272	0.00325	-0.84	0.4035	-0.00909	0.00366
CM2_C_OV	-0.00042	0.00301	-0.14	0.8885	-0.00633	0.00549
CM2_C_E	0.00313	0.00598	0.52	0.6007	-0.00859	0.01485
CM2_C_AV	0.00126	0.00386	0.33	0.7449	-0.00631	0.00883
CM3_C_OV	0.00248	0.00387	0.64	0.5211	-0.00511	0.01007
cCM3_C_E	-0.00021	0.00777	-0.03	0.9788	-0.01544	0.01503
CM3_C_AV	-0.00043	0.0051	-0.09	0.9321	-0.01043	0.00956
CM4_C_OV	-.00638**	0.00319	-2	0.0457	-0.01264	-0.00012
CM4_C_E	0.00348	0.00721	0.48	0.6297	-0.01066	0.01761
CM4_C_AV	0.00052	0.00511	0.1	0.9192	-0.00949	0.01053
Variance parameter given is sigma						
Std.Dev.	.04761***	0.00191	24.9	0	0.04386	0.05136

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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Random Coefficients LinearRg Model

Dependent variable LV_T

Log likelihood function 586.19281

Estimation based on N = 224, K = 23

Inf.Cr.AIC = -1126.4 AIC/N = -5.029

Unbalanced panel has 56 individuals

LINEAR regression model
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	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Nonrandom parameters						
C_AGE	0.00016	0.00013	1.26	0.2061	-0.00009	0.00042
TIME	0.00035	0.0011	0.32	0.7471	-0.00179	0.0025
Means for random parameters						
Constant/BASE	.01063***	0.0037	2.87	0.0041	0.00337	0.01788
CM2	0.00134	0.00404	0.33	0.7394	-0.00658	0.00927
CM3	0.00465	0.00374	1.24	0.2136	-0.00268	0.01198
CM4	-0.0027	0.00457	-0.59	0.5553	-0.01166	0.00627
Scale parameters for dist. Of random parameters						
Constant/BASE	.01362***	0.00107	12.67	0	0.01151	0.01572
CM2	0.00239	0.00195	1.23	0.2202	-0.00143	0.00622
CM3	.01590***	0.00167	9.55	0	0.01264	0.01916
CM4	0.00033	0.00196	0.17	0.8647	-0.00351	0.00418
Heterogeneity in the means of random parameters						
BASE_C_OV	.00172**	0.00076	2.25	0.0246	0.00022	0.00321
BASE_C_E	-0.00025	0.00147	-0.17	0.8635	-0.00313	0.00262
BASE_C_AV	-0.00078	0.0009	-0.87	0.3856	-0.00254	0.00098
CM2_C_OV	0.00101	0.00095	1.07	0.2836	-0.00084	0.00287
CM2_C_E	-0.00165	0.00188	-0.88	0.381	-0.00533	0.00204
CM2_C_AV	-0.00024	0.00133	-0.18	0.8545	-0.00285	0.00236
CM3_C_OV	0.00141	0.00098	1.43	0.1517	-0.00052	0.00333
cCM3_C_E	-.00332*	0.00183	-1.81	0.0705	-0.00691	0.00028
CM3_C_AV	-0.00107	0.00109	-0.98	0.3251	-0.0032	0.00106
CM4_C_OV	-0.00092	0.00136	-0.67	0.5004	-0.00358	0.00175
CM4_C_E	-0.00076	0.00274	-0.28	0.7811	-0.00613	0.00461
CM4_C_AV	0.00115	0.00173	0.66	0.5066	-0.00224	0.00454
Variance parameter given is sigma						
Std.Dev.	.01368***	0.00052	26.4	0	0.01266	0.01469

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Note: ***, **, * ==> Significance at 1%, 5%, 10% level.
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