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Francisco Emanuel Cunha Soares

Risk factors affecting pedestrian behaviour:
risk assessment in a virtual environment

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Professor Doctor Elisabete Fraga de Freitas
Doctor Emanuel Augusto Freitas de Sousa

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

I further declare that I have fully acknowledged the Code of Ethical Conduct of the University of Minho.

FATORES DE RISCO QUE AFETAM O COMPORTAMENTO DE PEÕES: AVALIAÇÃO DO RISCO EM AMBIENTE VIRTUAL

RESUMO

A promoção de modos de transporte suaves, dos quais fazem parte andar a pé ou de bicicleta, ultimamente tem sido impulsionada devido às vantagens sociais e ambientais que estes possuem. Por outro lado, o aumento dos volumes de tráfego motorizado verificado nos últimos anos tem-se traduzido num aumento da exposição ao risco de acidente para todos os utilizadores da rede viária. No que se refere aos peões, esse crescimento leva a que ocorram mais interações entre estes utilizadores da rede viária e os veículos motorizados. O número de mortes de peões que ocorrem nas estradas está longe de ser nulo, sendo que uma parte considerável delas acontece em passagens para peões. Procurar prevenir a ocorrência de acidentes que possam ter graves consequências, promovendo, desta forma, maior conforto e segurança para todos os utilizadores da rede viária deve ser uma prioridade, tendo ciente que o paradigma da mobilidade está a mudar.

Aproveitando as mais recentes tecnologias para a aquisição de dados sobre o comportamento de peões, como a análise automatizada de vídeo e o uso de um simulador onde num ambiente virtual se consegue estudar o comportamento dos peões quando executam o atravessamento da estrada sem que enfrentem um perigo real para a sua integridade física, o principal objetivo deste projeto de doutoramento foi a identificação e análise de fatores com influência no risco para peões quando atravessam a faixa de rodagem relacionados com as características das infraestruturas rodoviária e pedonal, as características do tráfego motorizado e pedonal e com o ruído emitido pelos veículos, dando particular relevância à tomada de decisão de atravessamento e à sua interação com os veículos.

De uma forma geral, os resultados mostram a influência direta ou indireta dos diversos fatores abordados na tomada de decisão dos peões e na interação entre eles e os veículos que deles se aproximam aquando do atravessamento da faixa de rodagem. No entanto, os resultados que mais se evidenciam levam a concluir que a velocidade e a cinemática dos veículos em aproximação à passagem para peões são fatores com elevada importância para a segurança pedonal.

Palavras-chave: Segurança rodoviária; Segurança pedonal; Decisão de atravessamento; Interação veículo-peão; Ambientes virtuais.

RISK FACTORS AFFECTING PEDESTRIAN BEHAVIOUR: RISK ASSESSMENT IN A VIRTUAL ENVIRONMENT

ABSTRACT

Soft modes of transportation, which include walking or cycling, have recently seen a boost in popularity and public promotion, due to their social and environmental advantages. This coincided with a growth of motorized traffic volumes in recent years, leading to more interactions between soft transportation users and motorized vehicles and greater exposure to the risk of accidents for all road users, with pedestrian being the most vulnerable ones. In fact, and despite a general trend of improvement in road safety, the number of pedestrian deaths occurring today is still substantial. A considerable part of them takes place in crosswalks. Identifying and analysing factors that may influence the behaviour of different road users is an important step in the process of designing changes to be made to the road infrastructure aiming to improve safety conditions. Trying to prevent accidents that could have serious consequences, and thus promoting greater comfort and safety for all road users, must be a priority, being aware that the mobility paradigm is changing with the emergence of different means of transport, namely electric vehicles.

Taking advantage of the latest technologies to acquire data on pedestrian behaviour, such as automated video analysis and an augmented reality simulator where in a virtual environment it is possible to study the behaviour of pedestrians when crossing the road without putting their physical integrity in real danger, the main objective of this PhD project was the identification and analysis of factors influencing the risk for pedestrians when crossing the road, giving particular relevance to decision-making on crossing and interaction with vehicles.

In general, the results show the direct or indirect influence of various factors and their interactions in the decision-making process of pedestrians when they cross a road. The most evident results lead to the conclusion that vehicle’s kinematics, especially its speed, are factors with high importance for pedestrian safety.

Keywords: Road safety; Pedestrian safety; Crossing decision; Vehicle-pedestrian interaction; Virtual environments.

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GLOSSARY

Time-to-passage (TTP): time remaining until an object (*e.g.* vehicle) passes in front of an observer (*e.g.* pedestrian), in seconds, if it continues with the speed and trajectory corresponding to the instant which the indicator is calculated (Hancock and Manser, 1998). The same as TTZ, TG, and T2 (Cavallo et al., 2019; Laureshyn et al., 2010; Lobjois and Cavallo, 2007; Várhelyi, 1998);

Minimum time-to-collision (TTC_{min}): minimum time remaining until a collision occurs, in seconds, if, during the encounter, road users (*e.g.* vehicle and pedestrian), continue with the speeds and trajectories that they had at the time for which the indicator was calculated (*e.g.* the instant that a pedestrian starts to cross the road) (Archer, 2005; Hayward, 1972; Horst, 1990);

Percentage of crossings: value resulting from the division between the number of crossings, i.e., the trials for which participants have clicked the computer mouse or started to cross the semi-virtual crosswalk before the vehicle has stopped or passed in front of them, and the total number of trials multiplied by one hundred. Its calculation was done per participant and for a given type of stimulus presented or a given movement condition of the approaching the vehicle in the experiences developed in a virtual environment;

Response time: time, in seconds, from the start of the stimulus presentation to the moment the participant clicked the mouse in the static experimental approach;

Crossing start time: time, in seconds, from the start of the stimulus presentation to the moment the participant started to cross the semi-virtual crosswalk in the dynamic experimental approach;

Static approach: experimental approach where participants performed a road crossing task by clicking on a button and standing at a predefined position during all the experiment;

Dynamic approach: experimental approach where participants performed a road crossing task walking along the semi-virtual crosswalk;

CPB sounds: sounds regarding the movement of a vehicle recorded by an Head and Torso Simulator following the Controlled Pass-By (CPB) method. These sounds include all vehicle noise sources, the effect of propagation mechanisms, and noise from the surrounding environment (Freitas et al., 2012);

CPX auralized sounds: sounds regarding the movement of a vehicle recorded by microphones type mounted on the back-right wheel of the vehicle following the Close Proximity (CPX) method. The signal captured by the CPX microphones is predominantly tyre-road noise. These sounds were then submitted to an auralization routine that outputs corresponding binaural CPB-like samples in order to allow a subject to hear a sound that appeared to come from an approaching vehicle.

1. INTRODUCTION

1.1. Background

1.1.1 Pedestrian fatalities in Portuguese and European roads

Road safety is today a major concern of many regulatory and governing entities through the world. This is motivated by the severe social and economic impacts resulting from traffic accidents and most importantly from road deaths and injuries they cause. The number of road fatalities has decreased in the European Union (EU) during the last 20 years as a result of a myriad of measures such as infrastructure improvements, wiser regulations and a constant demand for better safety features on the vehicles. However, according to the EU (European Commission, 2018b), the downward trend in the percentage of vulnerable road users' fatalities, particularly pedestrians, is not evolving as other indicators.

In the decade between 2007 and 2016, pedestrian fatalities decreased by 36 %, while the total number of road fatalities decreased by almost 41 % (European Commission, 2018b). The proportion of pedestrian traffic fatalities was still 21% in 2018 (CARE, 2020b; European Commission, 2018a), compared to the total of deaths occurred in the European roads. In Portugal, the downward trend was not as pronounced as in the group of the EU countries. The pedestrian fatalities were reduced by 10 %, while road fatalities decreased by 35 %. Furthermore, the percentage of pedestrian fatalities was above the European average. In 2016, 22 % of all deaths in the Portuguese roads were pedestrians (ANSR, 2007, 2016; European Commission, 2018b). That percentage had a small decrease in 2019 when 21 % of all road deaths were pedestrians (ANSR, 2019).

Coupled with those numbers, the ratio of 13.01 pedestrian fatalities per million population registered in 2019, higher than the European average, shows that Portugal is a country where there are still problems related to pedestrian safety (see Table 1.1). While the country fares substantially better than other European countries, such as Romania and Latvia, were 35.33 and 25.85 pedestrian fatalities per million people were reported, it is still far from the best placed ones, such as Netherlands and Sweden, where only 2.88 and 3.32 pedestrian fatalities per million population were registered (ANSR, 2019; CARE, 2020b).

Table 1.1 – Pedestrian fatality rates per million population by country of EU, consider the most recent available data (CARE, 2020b).

		All Road Users		**Pedestrians**		
	Year	**Mortal Victims**	**Deaths per million inhabitants**	**Mortal Victims**	**%**	**Deaths per million inhabitants**
Austria	2018	409	46.36	47	11.49	5.33
Belgium	2018	603	52.99	74	12.27	6.50
Bulgaria	2018	610	86.52	123	20.16	17.45
Croatia	2018	317	77.21	65	20.50	15.83
Cyprus	2018	49	56.70	8	16.33	9.26
Czech Rep.	2018	656	61.83	142	21.65	13.38
Denmark	2018	171	29.58	30	17.54	5.19
Estonia	2018	67	50.79	12	17.91	9.10
Finland	2018	239	43.35	25	10.46	4.53
France	2018	3246	50.15	468	14.42	7.23
Germany	2018	3275	39.56	464	14.17	5.60
Greece	2018	700	65.17	146	20.86	13.59
Hungary	2018	633	64.73	165	26.07	16.87
Ireland	2016	182	28.78	35	19.23	5.53
Italy	2018	3334	55.12	612	18.36	10.12
Latvia	2018	148	76.51	50	33.78	25.85
Lithuania	2016	242	66.00	81	33.47	22.09
Luxembourg	2018	36	59.80	3	8.33	4.98
Malta	2018	18	37.84	2	11.11	4.20
Netherlands	2018	593	34.81	49	8.26	2.88
Poland	2017	2831	75.36	873	30.84	23.24
Portugal	2019	626	60.80	134	21.41	13.01
Romania	2018	1867	95.59	690	36.96	35.33
Slovakia	2018	260	47.77	72	27.69	13.23
Slovenia	2018	91	44.03	13	14.29	6.29
Spain	2018	1806	38.71	386	21.37	8.27
Sweden	2018	309	32.02	32	10.36	3.32
U. Kingdom	2018	1839	28.00	472	25.67	7.19
EU	2018	24989	53.00	5221	20.89	11.07

Among all pedestrians killed on European roads, adults of 65 years or more are a significant concern. In 2016, 47 % of vulnerable road user's fatalities were elderly pedestrians. Fatalities in this age group have decreased by 25 % in the EU between 2007 and 2016, while the total number of pedestrian fatalities decreased by 36 %. Portugal, together with Greece and Italy, formed the group of countries where the percentage of elderly pedestrians killed in road accidents was higher, corresponding to 60% of the total pedestrian deaths in 2016 (European Commission, 2018b). In 2019, the percentage of elderly pedestrians' fatalities decreased to 58 % in Portugal (ANSR, 2019). According to European Commission (2018b), the reasons for the larger propensity of elderly pedestrians to suffer accidents could be the deteriorated locomotive functions, namely having slower movements, the decrease of muscular tone, the reduction in fine coordination, and the substantial diminution in the ability to adapt to sudden changes in posture, which characterize this age group. This adds to a generally higher fragility of elderly pedestrians since their bones are more brittle and their soft tissue less elastic.

Regarding sex, there is a slightly unbalanced difference in pedestrian fatalities between male and female pedestrians. In 2018, about 63 % of the pedestrian fatalities were male in all the European Union (CARE, 2020a). In Portugal, the number of pedestrian fatalities was less unbalanced in 2019, but still similar to the percentage verified for the total of European countries. 60 % of all pedestrian fatalities in the Portuguese roads were men (ANSR, 2019).

Another relevant aspect is the highest frequency of pedestrian deaths occurred in urban areas. In all 28 countries that were part of the European Union in 2018, 71 % of the registered pedestrian fatalities occurred in urban areas (CARE, 2020b). The greater risk exposure due to higher traffic volumes in those zones may be a cause for this. In Portugal, 81 % of the pedestrian fatalities happened in urban roads. Moreover, 20 % of the pedestrian fatalities in the Portuguese localities occurred when a pedestrian was crossing the road in a demarked crosswalk (ANSR, 2019), a place expected to provide safe road crossing conditions.

The numbers presented here show the need for practical work to be carried out on pedestrian safety. Many deaths are happening on the roads, particularly pedestrian deaths. The European Commission aims to reduce road deaths to almost zero by 2050 in an initiative that follows the Swedish policy and approach to road safety called "Vision Zero" (European Commission, 2020). The "Vision Zero" is based on the principle that road fatalities are not acceptable, but one should have into account that all humans make mistakes. This, accidents will always happen, but they must not result in serious human injury. This assumption should be the central pillar to be considered in the road system design. Dealing with human errors, considering them into the equations, “Vision Zero” is, overall, a strategy to follow during the design of the road system and related policies in order to ensure those inevitable mistakes do not result in severe injuries or fatalities, protecting all the road users and keeping them moving (FEVR, 2018; Swedish Transport Administration, 2010; Whitelegg and Haq, 2006).

1.1.2 Pedestrian safety studies

As the concept of sustainable mobility is becoming more popular, pedestrian traffic is increasing in importance, especially in large urban centres. There is now a tendency for regional and national governs to seek the increase of pedestrian activity and reduce the reliance on motorized vehicles. In this way, they expect to alleviate two of the biggest problems existing in large urban centres worldwide, namely traffic congestions and the environmental impacts caused by motorized vehicles. Besides, in large urban centres, walking is the most common mobility method, helping with the connexion between other modes of transportation, especially over short distances (Seco *et al.*, 2008). Beyond being a healthier option, it is also most environmental friendly one (Gupta and Pundir, 2015).

Pedestrians are very particular and distinct road users and defining safety measures to minimize their deaths and injuries is not as easy as for drivers, for example. Pedestrians can change their gait regarding direction or speed, which guarantees them great freedom of movement, giving them the capacity to move very easily and adapt to any route (Papadimitriou *et al.*, 2009). Despite being a major advantage of the pedestrian mode of transport, this characteristic is also considered a major problem to road safety due to the unpredictable reactions and behaviours (Seco *et al.*, 2008).

In this way, there is a need to better understand the pedestrian behaviour and movement characteristics along their travels to achieve the “Vision Zero” purpose. In the recent past, many studies have been developed focusing on the movement and behaviour of pedestrians during their travels and when they are crossing the road aiming to improve their safety conditions and to reduce the number of fatalities happening on the roads.

This subsection presents a general background of the types of approaches, the safety related indicators, the data collection methods more often used, and the risk factors more frequently addressed in pedestrian safety studies, aiming to support the information which is then presented in a more detailed way in the introductory section of each chapter.

1.1.2.1 Types of research approach

The studies on pedestrian safety are mainly based on a statistical analysis carried out through the construction of models. The impact of certain factors related to the characteristics of the infrastructure, of pedestrians and road traffic, and the characteristics of the surrounding environment on pedestrian safety has been analysed throughout statistical models of: (i) the number of pedestrian accidents, fatalities or injury severity; or (ii) the pedestrians' behaviour and their interaction with vehicles (Papadimitriou *et al.*, 2009).

Accident causes and severity have been widely analysed (*e.g.* (Amoh-Gyimah *et al.*, 2016; Dissanayake *et al.*, 2009; Haleem *et al.*, 2015; Kong and Yang, 2010; Kraidi and Evdorides, 2020; Olszewski *et al.*, 2015; Park and Ko, 2020; Pulugurtha and Sambhara, 2011; Quistberg *et al.*, 2015; Rosén and Sander, 2009; Stipancic *et al.*, 2020; Sze and Wong, 2007; Tay *et al.*, 2011; Ukkusuri *et al.*, 2012)), but there is a great issue concerning the collected data used in accident modelling.

To analyse accidents and their severity, quite complete accident databases are necessary to cover a significant number of variables. Accident databases are usually built by police crash records; however, accidents are rare, and not all are reported. This introduces a major bias, particularly for the study of vulnerable road users' safety, since accidents involving them happen more rarely, even though crashes have more severe consequences (Olszewski *et al.*, 2016). In addition, the reporting level is often incomplete, contains little information, and is randomly distributed regarding the type of road users involved, the location, and the severity of the accident (Elvik and Mysen, 1999; Shankar *et al.*, 2003; Svensson and Hydén, 2006). Furthermore, according to Svensson and Hydén (2006), the events' behavioural or situational aspects are not covered in police crash data. Accident reports only consider events with victims. Therefore, unsuccessful and successful interactive situations, for example road crossings, compliance to traffic signals, etc., should be analysed to get a more comprehensive understanding of the connection between behaviour and safety.

An option to fill this gap is to develop pedestrians' behaviour models. These models are designed to analyse the decision-making process, consider their choices, and speed and direction changes, during their travels or in specific situations with more relevance for their safety, for example when crossing the road (Ishaque and Noland, 2008; Papadimitriou *et al.*, 2009).

The study of pedestrian behaviour in a crossing situation has received a considerable interest by the researchers because crosswalks are places where there is a greater number of conflicts between pedestrians and vehicles. For this reason, the crosswalks are unsurprisingly places where a large number of accidents and pedestrian fatalities occur (ANSR, 2019; Lassarre *et al.*, 2007).

Usually, this type of study concerns the decision-making and crossing processes, including the interaction of these road users with motorized traffic. This type of research aims to identify the risk factors affecting pedestrian safety at crosswalks.

1.1.2.2 Safety related indicators

The identification of risk factors is often done through the analysis of indicators which are direct or indirectly related with the pedestrians' safety. Those indicators may be based in time, distances and/or in a combination of both (*e.g.* (Cavallo *et al.*, 2009; Connelly *et al.*, 1998; Deb *et al.*, 2017; Deb *et al.*, 2018b; Dietrich *et al.*, 2020; Dommes and Cavallo, 2011; Liu and Tung, 2014; Lobjois and Cavallo, 2007; Schwebel *et al.*, 2008; Schwebel *et al.*, 2012; Simpson *et al.*, 2003; Thomson *et al.*, 2005)), but also may be a qualitative or quantitative classification of pedestrians' individual actions, attitudes and behaviours, such as the pedestrian noncompliance to traffic lights (*e.g.* (Leden, 2002; Pešić *et al.*, 2016; Zhang *et al.*, 2016), crossing decision (*e.g.* (Barton *et al.*, 2012; Bernhoft and Carstensen, 2008; de Clercq *et al.*, 2019; Granié *et al.*, 2014; Holland and Hill, 2007; Meir *et al.*, 2015)), safe/unsafe decisions (*e.g.* (Cavallo *et al.*, 2009; Dommes and Cavallo, 2011; Dommes *et al.*, 2012)), number of collisions (*e.g.* (Cavallo *et al.*, 2019; Deb *et al.*, 2017; Schwebel *et al.*, 2012; Simpson *et al.*, 2003)), among others (see Appendix I – Summary table of all the cited studies about pedestrians' road crossing safety).

Most recently, the named surrogate safety indicators have been used. These indicators are meant to be alternatives or complements of analyses founded on accident records (Johnsson *et al.*, 2018a). The concept of surrogate safety indicators presumes that all traffic events involving proximity between two or more road users are related to safety. In turn, the traffic events are defined by the degree of severity related to the frequency of events (Hydén, 1987; Johnsson *et al.*, 2018a). According to this definition, the severity of an event ranges from the most severe degree, regarding a fatal accident which happens with low frequency, to the softest degree corresponding to a simple encounter between two road users which occurs more often, for instance, the interaction between a pedestrian and a vehicle in a crosswalk where no disturb to the pedestrian crossing happened (Svensson and Hydén, 2006).

According to Johnsson *et al.* (2018a), the existent surrogate safety indicators can be divided into three main groups: (i) those based on time-to-collision (TTC), which is defined as the time required for two road users to collide if they continue at their present speed and along the same path (Hayward, 1972; Laureshyn *et al.*, 2010); (ii) those founded on post-encroachment time (PET), defined as the time between the first road user leaving a common spatial zone (conflict zone) and the second arriving at it (Allen *et al.*, 1978; Cooper, 1984; Laureshyn *et al.*, 2010); and (iii) the deceleration-based indicators.

Regarding the first group, Johnsson *et al.* (2018a) include: the minimum time-to-collision (TTC_{min}) (Archer, 2005; Hayward, 1972; Horst, 1990); the time-to-accident (TA) (Hydén, 1977); the time-to-zebra (TTZ) (Várhelyi, 1998); the time-exposed TTC (TET) (Minderhoud and Bovy, 2001); the time-integrated TTC (TIT) (Minderhoud and Bovy, 2001); and the T2 (Laureshyn *et al.*, 2010). The group of the PET-based indicators mentioned by Johnsson *et al.* (2018a) considers: the time gap (TG) (Allen *et al.*, 1978; Vogel, 2002); the encroachment time (ET) (Allen *et al.*, 1978); the conflict index (CI) (Alhajyaseen, 2015); and the time advantage (TAdv) (Laureshyn *et al.*, 2010). The indicators belonging to the deceleration-based group are: the deceleration to safety time (DST) (Hupfer, 1997); the deceleration rate (DR) (Gettman and Head, 2003); the jerk profile and the yaw rate (Tageldin *et al.*, 2015).

With a definition similar to that of TTZ, there are the time-to-arrive (TTA) (Schiff and Oldak, 1990) and the time-to-passage (TTP) (Hancock and Manser, 1998). Both concepts and their nomenclatures are more frequently used in other scientific areas; however, their applicability is not called into question for road safety research.

1.1.2.3 Data collection methods

Another relevant aspect regarding the studies on pedestrian safety at crosswalks is the data collection method. According to Papadimitriou *et al.* (2016b), methods for analysing pedestrian behaviour can be divided into those based on field observations or surveys. Most recently, Deb *et al.* (2018a) and Feng *et* *al.* (2021) identified a new group of methods in different reviews of data collection methods used in studies about pedestrian behaviour: the controlled experiments, which may be split into naturalistic experimentation and simulation.

Regarding pedestrians' field observations when crossing the road, they can be used to get rich information about road users' movement and behaviour. However, since this method does not involve all variables' control, many observations are necessary, which can make data collection and analysis very time-consuming (Feng *et al.*, 2021). The most common way of gathering this data is through video recordings of crossing situations (Lassarre *et al.*, 2012). Video automated or semi-automated processing and analysis tools have lately started to turn field observations into a more efficient method (*e.g.* (Ismail *et al.*, 2009; Jackson *et al.*, 2013; Johnsson *et al.*, 2018b; Saunier *et al.*, 2010)). As referred by Olszewski *et al.* (2016), these tools are habitually used due to their versatility, low cost, and the content of the data they can export. However, video recordings are limited to the camera's field of vision. Usually, the road users are detected in an area of 30 – 40 m wide. High levels of luminosity, fog, rain, snow, and night-time, may jeopardize or even prevent the data collection (Olszewski *et al.*, 2016).

Other alternatives to video analysis are following pedestrians' trajectory through GPS instruments or Bluetooth/Wi-Fi sensors. These tools present some limitations compared to video analysis, namely problems with precise location, unavailability of information regarding traffic conditions, and they can influence the users' behaviour, since they imply pedestrians' instrumentation (Feng *et al.*, 2021; Papadimitriou *et al.*, 2016a).

As said by Deb *et al.* (2018a), surveys can be written documents, online questionnaires, face-to-face interviews, or telephone interviews. This type of method allows for great controllability of all the variables inserted in a study since researchers' questions in a survey are previously design. However, the answers given by participants may not portrait their actions in real situations. This method is useful to complement the data gathered in field observations or controlled experimentation because it provides the opportunity to acquire information about pedestrians' personal and psychological characteristics (Feng *et al.*, 2021).

Controlled experiments comprise the most used semi-controlled naturalistic experiments and virtual reality experiments (Deb *et al.*, 2018a; Feng *et al.*, 2021; Kircher *et al.*, 2017). Beyond many advantages, both have the disadvantage that they may cause participants' behaviour to be unrealistic since they aware that they are being observed and analysed, such as in the usage of surveys (Feng *et al.*, 2021).

According to Kircher *et al.* (2017), semi-controlled studies follow a hybrid approach between controlled experiments and observational methods. In semi-controlled naturalistic experiments, the researcher can previously define groups of participants, routes, and tasks. However, there is a set of uncontrolled variables present, for instance, vehicle speeds, traffic volumes, pedestrian and motorized traffic densities, etc. This method is usually applied to analyse factors such as gait parameters and pedestrian spatial organization in real environments (Cao *et al.*, 2018; Fu *et al.*, 2019; Wei *et al.*, 2015). The relatively high controllability of variables makes this experimental method the most effective in providing complete information to analyse particular factors (Feng *et al.*, 2021; Kircher *et al.*, 2017). However, the lack of precise control of all the variables involved in the study can turn the analysis of those factors complicated (Kircher *et al.*, 2017). In addition, this method requires setting up data collection devices, which is labour intensive (Feng *et al.*, 2021).

Virtual reality experiments have been used in situations where real-world environments are difficult to control or dangerous (Deb *et al.*, 2017). Schwebel *et al.* (2008), citing Reid (2002), define virtual reality "as a computer- or video-generated environment that gives the user a sense of being in a displayed virtual world through realistic images, high-quality sound, the feeling of immersion, and the ability to interact with the virtual world". The use of this tool in controlled experiments allows the simulation of the more diverse situations, where all the variables can be easily controlled since the virtual scenes can be quickly built and modified (Deb *et al.*, 2017; Feng *et al.*, 2021). Virtual reality experiments allow the recreation in controlled experimental settings of risky situations, such road crossings, but without exposing the participants to a real risk (Deb *et al.*, 2017; Schwebel *et al.*, 2008). Compared to the other data collection methods, this allows for a more accurate data collection due to the mentioned controllability. Furthermore, that data can be easily processed and quickly analysed (Feng *et al.*, 2021). However, simulators are expensive in set-up and maintenance. They require custom-built solutions (Deb *et al.*, 2017), which need sufficient space to consider participants' movement during the experiments.

1.1.2.4 Risk factors

The risk factors associated with pedestrian behaviour and safety identified in the literature are vast. But, regarding the ones more often addressed, they are essentially distributed into three distinct groups: those concerning the characteristics of pedestrians themselves, those regarding the characteristics of the road and built environment, and the factors related to traffic characteristics.

Within the group of pedestrian characteristics, pedestrians' age and sex have been the most addressed factors. Some authors refer that young pedestrians are more likely to make unsafe crossing decisions than older pedestrians because of the lack of experience, unpredictable behaviours, distraction, and poor risk perception (Bernhoft and Carstensen, 2008; Ezzati Amini *et al.*, 2019; Holland and Hill, 2007; Johansson *et al.*, 2004; Moyano Díaz, 2002; Rosenbloom *et al.*, 2008). Regarding pedestrians' sex, the conclusions are not consensual. However, when differences between female and male risk-taking behaviours are found, females are generally more conservative than males, acting more safely (Hamed, 2001; Holland and Hill, 2007; Moyano Díaz, 2002; Papadimitriou *et al.*, 2016b). A few studies have also reported effects of pedestrians' cultural, socioeconomic, and educational profile. However, these factors are difficult to analyse properly as such analysis requires considerable data collection of the same indicators at different points of the globe or a comparison of studies with similar methods and approaches to obtain reliable results (Sueur *et al.*, 2013).

Concerning the characteristics of the road and built environment, road width, the number of lanes, the function of the surrounding buildings, the width and quality of the sidewalks, the marked parking places, and various pedestrian engineering and crossing treatments are factors which some authors argue that may directly or indirectly influence the pedestrian safety and their crossing interaction with vehicles (Ewing and Dumbaugh, 2009; Granié *et al.*, 2014; Lin *et al.*, 2015; Sucha *et al.*, 2017; Turner *et al.*, 2006; Zegeer *et al.*, 2006). Pedestrians may feel safer when the road width is shorter and the number of lanes is lower (Sucha *et al.*, 2017; Turner *et al.*, 2006; Zegeer *et al.*, 2006). In contrast, the lack of shops and the small number of houses, tight sidewalks or lateral space dedicated to pedestrians, the inexistence of marked parking places in the area involving the crosswalk are all factors that lead pedestrians to feel uncomfortable and to consider unsafe to cross the road. With all of these features which usually characterize an unattractive zone to walk, pedestrians infer a low density of pedestrian traffic, which they relate to the existence of better conditions to the practice of higher speeds by drivers (Granié *et al.*, 2014).

Pedestrian and motorized traffic characteristics can influence pedestrian safety, impacting from pedestrian crossing decision-making to the occurrence of accidents. According to Ezzati Amini *et al.* (2019) and Sucha *et al.* (2017), pedestrians consider traffic density a factor when making the crossing decision. High motorized traffic volumes are considered riskier to pedestrians since the likelihood of accident and their injury severity, increases with the number of vehicles passing by a determined placed (LaScala *et al.*, 2000; Leden, 2002; Papadimitriou *et al.*, 2012). Additionally, drivers' tendency to yield at crosswalks also decreases with high motorized traffic volumes (Sucha *et al.*, 2017). Pedestrian traffic volumes have a contrary effect on their safety. According to Leden (2002), the risk of an accident involving pedestrians decreases with increasing pedestrian flows. The author argues that one explanation could be the higher driver alertness about the presence of pedestrians. However, if not accompanied by appropriate traffic and safety conditions, the higher pedestrian traffic volumes can lead to more pedestrian accidents (Leden, 2002).

On the other hand, for some authors, the vehicle approaching speed is one of the most important factors, if not the most, used by pedestrians to explain their crossing decision (Granié *et al.*, 2014; Sucha *et al.*, 2017). According to Várhelyi (1998), the vehicle speed is the unique single factor relevant to pedestrian safety and feeling of safety. It can affect their crossing decision and behaviour, since a fast-approaching vehicle can pressure pedestrians and might force them to cross the road unsafely. Furthermore, although pedestrians are aware that due consideration should be given to vehicle speed when making crossing decisions, they may not perceive the vehicle speed and misjudge the gap time available to cross the road (Liu and Tung, 2014).

Other factor which has been attracting the efforts of some researchers is the vehicle noise. People are used to vehicles making noise because until very recently there were only vehicles with combustion engines in worldwide roads. With the appearance of electric and hybrid vehicles, noise levels emitted are reduced (Verheijen and Jabben, 2010; Wogalter *et al.*, 2001). What, on the one hand, can be considered a positive aspect given the negative impact that traffic noise has directly or indirectly on human health, on the other hand, it can be a serious problem from the point of view of road safety. Vehicular noise often acts as a cue for vulnerable road users, helping them to detect and locate the approaching vehicles and improving their perception of speed and distance. Thus, lower noise emissions can put pedestrian safety at risk, particularly blind or vision impaired ones (Barton *et al.*, 2013; Barton *et al.*, 2012; Emerson *et al.*, 2013; Emerson *et al.*, 2011; Verheijen and Jabben, 2010; Wiener *et al.*, 2006).

Appendix I presents a table summarizing the data collection methods, the safety and behavioural indicators, and the factors addressed in all the studies about pedestrians' crossing safety cited throughout this document.

1.2. Objectives

As previously exposed, the numbers of pedestrian fatalities that occur on the roads, particularly in Portugal and throughout the European Union, are worrying. Therefore, questions about pedestrian safety, the interaction of pedestrians with motorized traffic, and their operational effects need to be explored. In this sense, understanding the pedestrian behaviour in urban environments, especially when crossing the road, is an essential issue to achieve the desired purposes of "Vision Zero".

Taking advantage of the latest technologies for the data acquisition on pedestrian behaviour, such as automated video analysis and the use of simulators and the previously mentioned indicators, the general objective of this doctoral project was the identification and analysis of risk factors for pedestrians when crossing the road, with a particular focus on their crossing decision-making and interaction with vehicles approaching the crosswalk.

This document is composed of several chapters that explore gaps in the existing literature. Those gaps are identified in the introduction section of each one of them. Nevertheless, according to the data collection methodology about the pedestrians' behaviour at road crossings, the work can be divided into two distinct parts. One part based on field observation, which was performed through video recordings; and another based on controlled experiments carried out in a virtual environment.

In addition to the transversal objective of this doctoral project, the field observation aimed to collect data on the vehicles' movement approaching the crosswalk to achieve the following primary objectives of this work: the construction of the simulator to be used in controlled experiences; and to identify vehicle-pedestrian interactions risk factors related to the pedestrians' demographic, the road and pedestrian infrastructure, and the pedestrian and motorized traffic characteristics. In this way, the weights of these factors can be evaluated after a careful selection, using a more in-depth analysis performed in a virtual environment.

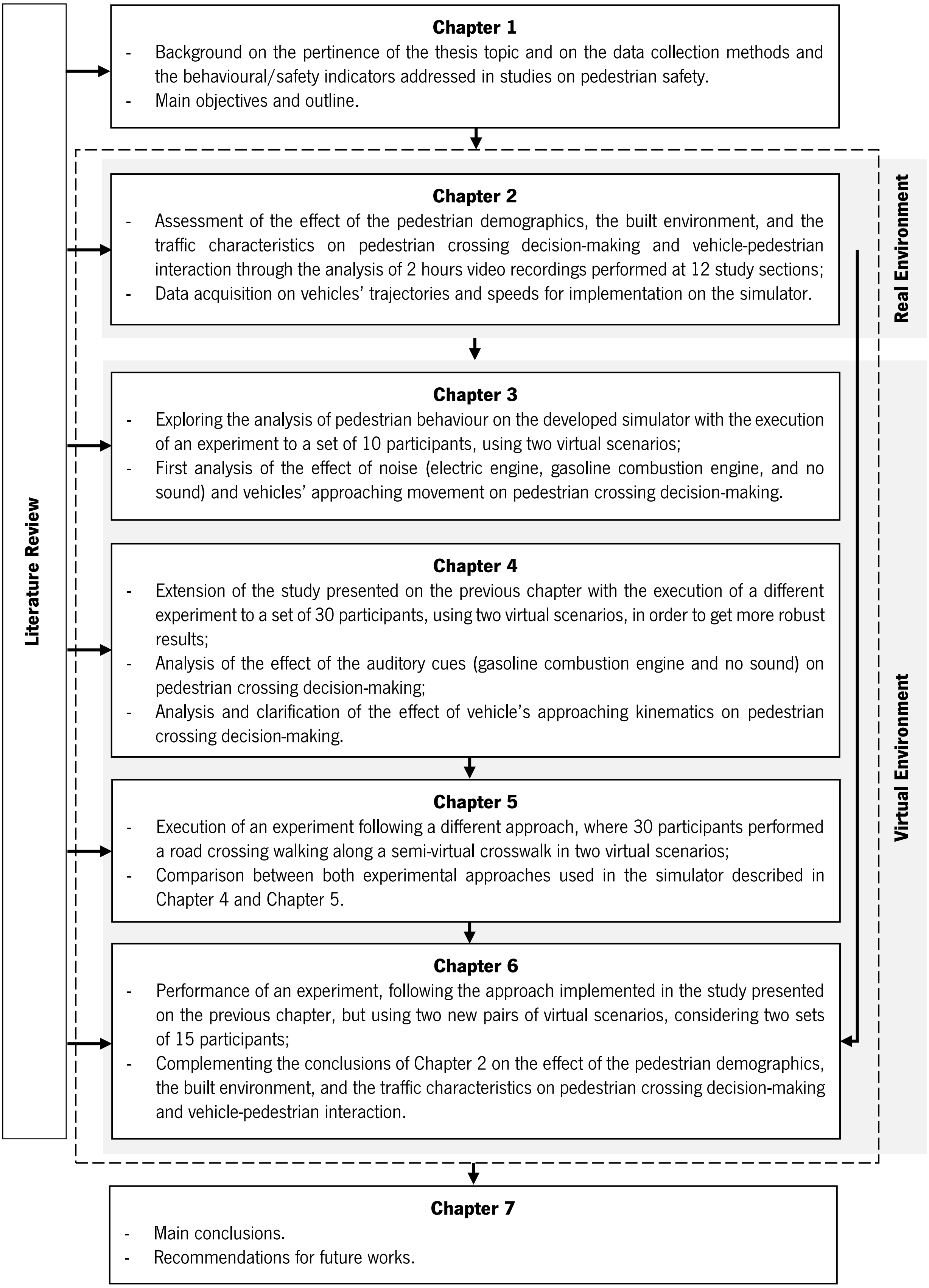
The goals of the controlled experiments were to evaluate how the noise emitted by the approaching vehicles and their approaching movement pattern can affect the pedestrians' crossing decision-making, and to complement the identification of factors associated with the pedestrians' demographics, the road, and the pedestrian infrastructure characteristics, not neglecting the speed of approach of vehicles, influencing the pedestrians crossing decision-making, as well as their interaction with vehicles, carried out in the real environment part of this study.

1.3. Outline

The conducted scientific research work described on this thesis is organized into seven chapters. The overall research methodology is presented in Figure 1.1 and it incorporates three main tasks: (i) literature review; (ii) analysis of pedestrian behaviour in a real environment; and (iii) analysis of pedestrian behaviour in a virtual environment.

The present chapter (Chapter 1) contains a brief background and review of pedestrian fatalities in EU and Portugal, of the safety and behavioural indicators, the data collection methods usually, and the risk factors more often addressed and used in pedestrian road crossing safety studies. This chapter aims to support the introduction and the methodology sections of Chapter 2, 3, 4, 5 and 6. Then, it specifies the work's main objectives and ends with a summary of the content of this thesis.

Chapter 2 presents a study carried out in a real environment where data from vehicle-pedestrian interaction were collected through video recordings in twelve different crosswalks. The pedestrian crossing decision-making and the severity of the encounters between them and vehicles were analysed in terms of TTP and TTC_{min}, respectively. Given the wide range of risk factors identified in the literature, the aim of the analysis carried out in this chapter was to identify risk factors to vehicle-pedestrian interactions related to the pedestrians' demographics, the road and pedestrian infrastructures, motorized and pedestrian traffic characteristics, during road crossings at unsignalized crosswalks, in order to select them for a more in-depth evaluation in the following chapters. A special focus was given to vehicles' approaching speed. The data collected about vehicles' trajectories and speeds were used to configure the virtual scenarios used in the simulator (Chapter 3, 4, 5, and 6).



Chapter 1
- Background on the pertinence of the thesis topic and on the data collection methods and the behavioural/safety indicators addressed in studies on pedestrian safety.
- Main objectives and outline.

Chapter 2
- Assessment of the effect of the pedestrian demographics, the built environment, and the traffic characteristics on pedestrian crossing decision-making and vehicle-pedestrian interaction through the analysis of 2 hours video recordings performed at 12 study sections;
- Data acquisition on vehicles' trajectories and speeds for implementation on the simulator.

Chapter 3
- Exploring the analysis of pedestrian behaviour on the developed simulator with the execution of an experiment to a set of 10 participants, using two virtual scenarios;
- First analysis of the effect of noise (electric engine, gasoline combustion engine, and no sound) and vehicles' approaching movement on pedestrian crossing decision-making.

Chapter 4
- Extension of the study presented on the previous chapter with the execution of a different experiment to a set of 30 participants, using two virtual scenarios, in order to get more robust results;
- Analysis of the effect of the auditory cues (gasoline combustion engine and no sound) on pedestrian crossing decision-making;
- Analysis and clarification of the effect of vehicle's approaching kinematics on pedestrian crossing decision-making.

Chapter 5
- Execution of an experiment following a different approach, where 30 participants performed a road crossing walking along a semi-virtual crosswalk in two virtual scenarios;
- Comparison between both experimental approaches used in the simulator described in Chapter 4 and Chapter 5.

Chapter 6
- Performance of an experiment, following the approach implemented in the study presented on the previous chapter, but using two new pairs of virtual scenarios, considering two sets of 15 participants;
- Complementing the conclusions of Chapter 2 on the effect of the pedestrian demographics, the built environment, and the traffic characteristics on pedestrian crossing decision-making and vehicle-pedestrian interaction.

Chapter 7
- Main conclusions.
- Recommendations for future works.

Figure 1.1 – Research methodology and thesis overview.

Chapter 3 comprises a first approach to analyse pedestrian behaviour using the developed simulator. Given the relevance that electric vehicles and traffic noise have received in recent times and the existence of a literature gap regarding the simulation of the movement of vehicles approaching the crosswalk in studies using a virtual environment to assess pedestrians' behaviour and safety, this chapter aimed to analyse the influence of vehicular noise, as well as vehicle's approaching speeds and trajectories, on pedestrian crossing decision-making. The importance of the vehicle's approaching movement and the auditory cues on pedestrian crossing decision-making was analysed in terms of percentage of crossings, response time, and TTP. Three auditory conditions, three vehicle's movement conditions, and two scenarios were depicted in the ninety stimuli presented to a reduced sample of ten participants which performed an experimental task of a road crossing situation standing at a predefined position and clicking in a computer mouse when intended to cross the virtual road. This experimental approach was called "Static approach".

Chapter 4 consists of an extension of the study presented in Chapter 3, intending to confirm its results through a more robust data sample. Considering the gaps in the literature and the reduced relevance given to factors such as the auditory cues and the vehicle's approaching movement as a starting point, the aim of the work presented in the Chapter 4 was to clarify the role of the vehicle kinematics on pedestrians' crossing decision-making, mediated by the resulting visual and auditory cues. A more thorough analysis of the role of speed and distance, as well as the different speed profiles of the approaching vehicle was performed. Such as in Chapter 3, the effect of the approaching movement and the noise emitted by the vehicle on pedestrian crossing decision-making was also analysed in terms of percentage of crossings, response time, and TTP. Two auditory conditions, ten vehicle's movement conditions, and two scenarios were depicted in the two-hundred stimuli presented to thirty participants.

Chapter 5 describes a methodological study where two experimental approaches are compared: (i) the approach used in Chapter 3 and Chapter 4, where participants performed a road crossing task by clicking on a button and standing at a predefined position during all the experiment (Static approach); (ii) an approach where participants performed the same task walking along the virtual crosswalk, called "Dynamic approach". The aim of this analysis was to evaluate the impact of the implementation of a more realistic approach for studying pedestrian crossing behaviour and to assess the advantages or disadvantages of the use of each approach, since both are more frequently used in pedestrian safety studies. The data collected in the study presented in Chapter 4 from the thirty participants was compared to that collected from another thirty participants who performed the experiment following a different approach in terms of percentage of crossings, response time, and TTP. Subsequently, the TTP obtained in the virtual environments was compared to those obtained in a real environment.

Chapter 6 is based on an extension of the virtual environment of the study presented in Chapter 2. The experimental protocol related to the dynamic experience introduced and presented in the study described on Chapter 5 was considered to assess the risk factors to vehicle-pedestrian interactions related to the pedestrians' demographics, the road and pedestrian infrastructures, motorized and pedestrian traffic characteristics, during road crossings in order to complement the findings of the analysis of pedestrian behaviour in the real environments (Chapter 2). The pedestrian crossing decision and the severity of the encounters between them and the vehicle were analysed in terms of percentage of crossings, crossing start time, percentage of crashes, TTP, and TTC_{min}. Fifty stimuli were presented in six different scenarios to a total of forty-five participants.

Although the conclusions are included in each chapter, a summary of the work carried out and its main conclusion are presented in Chapter 7. It is also given a set of recommendations for future works.

2. ANALYSIS OF PEDESTRIAN BEHAVIOUR IN REAL ENVIRONMENT

2.1. Introduction

During the last years, governing bodies in several countries have been trying to improve road safety, by raising awareness of road users and thus trying to improve behaviours or by making changes to road infrastructure. Greater attention is provided to users of soft modes of transport, which include cyclists and pedestrians, since they are the most vulnerable to road accidents. Still, accidents continue to be frequent and more needs to be done. Identifying and analysing factors that may influence road users' behaviour is an essential step in designing road infrastructure changes and public policies to improve safety conditions.

Regarding pedestrian safety, exploring the interaction of these road users with the motorized traffic is key to understand what may affect their safety and put their integrity and life at risk. Several studies have been carried out addressing pedestrian behaviour, especially during road crossing situations, because most of the accidents involving pedestrians happen in those situations. Crosswalks are places where a bigger number of conflicts between pedestrians and road traffic occurs and, thus, where these vulnerable road users are more exposed to the risk of accident (Lassarre *et al.*, 2007).

Following that which is described in Chapter 1, the risk factors associated with pedestrian behaviour and safety are vast. They are distributed into three distinct groups: those concerning the pedestrians' characteristics, those regarding the characteristics of the road and built environment, and the factors related to traffic characteristics.

Within the group of pedestrian characteristics, pedestrians' age and sex have been the most addressed factors (Bernhoft and Carstensen, 2008; Ezzati Amini *et al.*, 2019; Hamed, 2001; Holland and Hill, 2007; Johansson *et al.*, 2004; Moyano Díaz, 2002; Papadimitriou *et al.*, 2016b; Rosenbloom *et al.*, 2008). Pedestrians' cultural, socioeconomic, and educational profile are other factors sometimes considered in pedestrian safety studies (Sueur *et al.*, 2013).

Concerning the characteristics of the road and built environment, the road width, the number of lanes, the function of the surrounding buildings, the width and quality of the sidewalks, the marked parking places, and various pedestrian engineering and crossing treatments are the more studied factors (Ewing and Dumbaugh, 2009; Granié *et al.*, 2014; Lin *et al.*, 2015; Sucha *et al.*, 2017; Turner *et al.*, 2006; Zegeer *et al.*, 2006).

Regarding pedestrian and motorized traffic characteristics, some of the more often studied factors are: traffic density (Ezzati Amini *et al.*, 2019; Sucha *et al.*, 2017), traffic volumes (LaScala *et al.*, 2000; Leden, 2002; Papadimitriou *et al.*, 2012; Sucha *et al.*, 2017), vehicles' speed (Granié *et al.*, 2014; Liu and Tung, 2014; Sucha *et al.*, 2017; Várhelyi, 1998), and traffic noise (Barton *et al.*, 2013; Barton *et al.*, 2012; Emerson *et al.*, 2013; Emerson *et al.*, 2011; Verheijen and Jabben, 2010; Wiener *et al.*, 2006; Wogalter *et al.*, 2001).

The work reported in this chapter aimed to identify risk factors to vehicle-pedestrian interactions during road crossings at unsignalized crosswalks, selecting them for future evaluation of their weights using a more in-depth analysis performed in a virtual environment. An analysis of the influence of various factors related to the pedestrians' demographic, the road and pedestrian infrastructures, motorized and pedestrian traffic characteristics in pedestrian crossing decision-making and their interaction with motorized vehicles is performed.

According to Johnsson *et al.* (2018a), accident analysis based on public records is the most direct and common method of assessing road safety, and the same is true for pedestrian safety. Nevertheless, this method has at least two limitations: the randomness of accidents, which limits the analysis regarding the amount of data (Elvik, 2009), and the fact that not all accidents are reported (Elvik and Mysen, 1999). The latter becomes a major bias for the study of vulnerable road users' safety, since vehicle-pedestrian accidents happens more rarely than vehicle-vehicle ones, even though they normally have more severe consequences (Olszewski *et al.*, 2016).

As described in Chapter 1, surrogate safety indicators are currently being used as alternative or complementary methods in identifying factors that can impact the road users' risk or behaviour (Johnsson *et al.*, 2018a). Examples of such indicators are TTC and PET (Allen *et al.*, 1978; Cooper, 1984; Hayward, 1972; Horst, 1990; Hydén, 1977). More recently, indicators focusing on conflicts between motorized vehicles and vulnerable users have been proposed, such as the TTZ, TG, TA, and the PRI (Cafiso *et al.*, 2011; Cavallo *et al.*, 2019; Lobjois and Cavallo, 2007; Várhelyi, 1998).

In this study, video recordings were done in twelve different streets and were then analysed by an automated video analysis software to collect data about trajectories and speeds of pedestrians crossing the road and vehicles approaching the crosswalk. The influence of the several factors belonging to the groups above-mentioned on pedestrian crossing decision-making and interaction with the approaching vehicles was then carried out through the construction of a set of statistical models. TTC_{min} and TTP were used to assess the severity of vehicle-pedestrian encounters and pedestrian crossing decision, respectively.

2.2. Materials and Methods

2.2.1 Selection of study sections

Six pedestrian crosswalks located in the city Guimarães and six others in the city of Braga were chosen as study sections. These sites were selected based on the intersections' characteristics and surroundings, by analysing the statistics of accidents between 2009 and 2015. Streets names have been abbreviated to make data visualization and interpretation easier (Table 2.1).

Table 2.1 – Name of each street and its identification.

Guimarães		**Braga**	
Street	**Abbreviation**	**Street**	**Abbreviation**
Rua Teixeira de Pascoais	TP	Rua 25 de Abril	25A
Av. de São Gonçalo	SG	Rua Conselheiro Lobato	CL
Rua Alm. Gago Coutinho	AGC	Rua D. Bento Martins Jr.	BMJ
Rua da Guiné	G	Rua Doutor Costa Júnior	CJ
Rua do Picoto	P	Av. Gen. Norton de Matos	GNM
Avenida de Londres	L	Rua Nova de Santa Cruz	NSC

The following characteristics of the considered streets were registered (see Table 2.2 and Table 2.3):

- Length of the crosswalk: transversal distance measured between the two ends (curbs) of the demarked crosswalk, in meters [m];
- Average width of the traffic lanes: mean value of the transversal dimension of road lanes, in meters [m];
- Width of the street to park: transversal width of the street occupied by demarked parking places, in meters [m];
- Average width of the sidewalk: mean value of the transversal dimension of sidewalks, in meters [m];
- Width of the crosswalk: longitudinal dimension (perpendicular to the pedestrians' crossing movement) of the demarked crosswalk, in meters [m];
- Directions of the road: number of the road traffic directions;
- Distance to a bus stop: the distance between the centre of the crosswalk and the nearest bus stop, in meters [m];
- Road pavement: type of the road surface;
- Road classification: category of the road according to its function and characteristics;
- Number of traffic lanes: number of lanes composing the road.

Table 2.2 – Main characteristics of each one of the six streets in Guimarães.

	Street					
	TP	**SG**	**AGC**	**G**	**P**	**L**
Length of the crosswalk (m)	7.13	12.5	7.03	6.16	7.73	7.21
Average width of the lanes (m)	3.57	3.00	2.56	3.08	3.87	3.61
Width of the street to park (m)	10.12	5.17	7.15	0	0	4.55
Average width of the sidewalk (m)	4.11	2.96	1.95	1.67	1.77	5.85
Width of the crosswalk (m)	5.12	5.35	3.54	3.29	4.05	4.14
Directions of the road	2	2	2	2	1	1
Distance to a bus stop (m)	104.30	18.70	15.30	34.20	126	22.40
Road pavement[1]	AC	AC	CS	AC	AC	AC
Road classification[2]	C	C	L	L	C	C
Number of lanes	2	4	2	2	2	2

[1] AC – Asphalt concrete; CS – Cobblestones.

[2] C – Collector; L – Local road.

Table 2.3 – Main characteristics of each one of the six streets in Braga.

	Street					
	25A	**CL**	**BMJ**	**CJ**	**GNM**	**NSC**
Length of the crosswalk (m)	7.85	8.97	9.96	5.21	13.80	10.03
Average width of the lanes (m)	2.87	3.32	3.26	2.61	2.90	3.05
Width of the street to park (m)	4.23	2.34	1.92	0	2.20	0
Average width of the Sidewalk (m)	4.17	1.32	1.52	1.55	5.24	6.57
Width of the crosswalk (m)	3.40	3.00	3.04	3.33	2.64	4.48
Directions of the road	1	1	2	2	2	2
Distance to a bus stop(m)	48.50	46.10	50.70	87.60	195.20	42.90
Road pavement[1]	AC	AC	AC	CS	AC	AC
Road classification[2]	L	C	C	L	C	L
Number of lanes	2	2	2	2	4	2

[1] AC – Asphalt concrete; CS – Cobblestones.
[2] C – Collector; L – Local road.

The length of the crosswalk, the width of the road and the lanes, the width of the street used for parking places, the average width of the sidewalks, and the width of the crosswalk were measured on-site.

2.2.2 Video recordings

The video recordings lasted 2 hours on each one of the twelve streets where the selected study sections were located. Simultaneously to the video recordings, the pedestrian and motorized traffic volumes were counted in each street (Table 2.4 and Table 2.5). The execution of this task was only possible due to the Guimarães and Braga Municipalities' collaboration, provided human resources and equipment to the camera installation.

Table 2.4 – Pedestrian and motorized traffic volumes of each one of the six streets in Guimarães.

	Street					
	TP	**SG**	**AGC**	**G**	**P**	**L**
Motorized traffic volume[1] (veh/h)	1286[d]	518[c]	108[c]	527[c]	617[c]	760[b]
Pedestrian traffic volume[1] (ped/h)	325[d]	251[c]	62[c]	31[c]	85[c]	65[b]

[1] Traffic counts performed at: (a) 8:30 -10:30; (b) 11:30 - 13:30; (c) 13:30 - 15:30; and (d) 17:00 - 19:00.

Table 2.5 – Pedestrian and motorized traffic volumes of each one of the six streets in Braga.

	Street					
	25A	**CL**	**BMJ**	**CJ**	**GNM**	**NSC**
Motorized traffic volume[1] (veh/h)	784[d]	579[b]	595[a]	132[c]	528[a]	582[c]
Pedestrian traffic volume[1] (ped/h)	276[d]	82[b]	54[a]	42[c]	48[a]	631[c]

[1] Traffic counts performed at: (a) 8:30 -10:30; (b) 11:30 - 13:30; (c) 13:30 - 15:30; and (d) 17:00 - 19:00.

The video camera was placed at the height of over 5 m, hung up on light poles, and at a distance between 15 and 25 m from the crosswalk, depending on each location's conditions. Figure 2.1 shows an example of the video camera's placement. Figure 2.2 and Figure 2.3 show a frame from the recorded videos on the twelve streets.

The demographic characteristics of pedestrians, sex and age, were also considered in the data extraction process. Since pedestrians' sex and age were determined by direct observation, four distinct age groups were examined to reduce age estimation error (< 20 years; 20 - 40 years; 40 - 60 years; and > 60 years).

Figure 2.1 – Example of the video camera's placement (BMJ street, Braga).

(a) (b) (c) (d) (e) (f)

Figure 2.2 – Video frame from the six streets considered in Guimarães: (a) TP; (b) SG; (c) AGC; (d) G; (e) P; (f) L.

(a) (b)

(c) (d)

(e) (f)

Figure 2.3 – Video frame from the six streets considered in Braga: (a) 25A; (b) CL; (c) BMJ; (d) CJ; (e) GNM; (f) NSC.

2.2.3 Video analysis

Video analysis was carried out through the Traffic Intelligence program (Ismail *et al.*, 2009; Jackson *et al.*, 2013; Saunier *et al.*, 2010) (Figure 2.4). In essence, for each recorded video, the program identified and mapped the motion of each pixel, frame by frame, grouped them by the similarity of characteristics, and classified each group as an object (pedestrian or vehicle), thus obtaining the cars and pedestrians' trajectories and speeds.

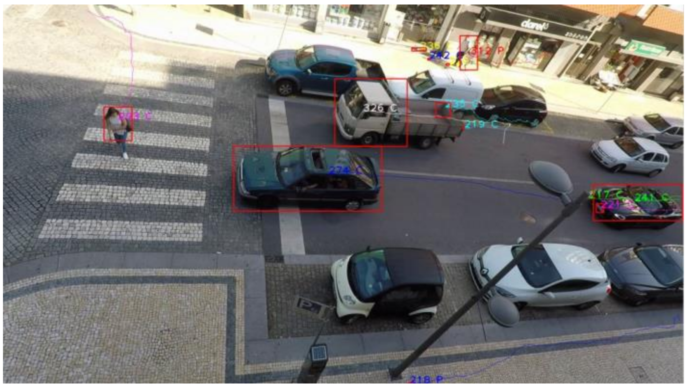


Figure 2.4 – Example of the video analysis made through Traffic Intelligence (BMJ street, Braga).

Other tasks were inherent to the process of video analysis, such as camera calibration, which consists of extracting the matrix and calculating its distortion coefficients, and the points homography, which corresponded to associating the video coordinates with the real-world coordinates.

Before the tasks previously mentioned, the videos needed to be converted into MOG 2. MOG 2 creation process consists of a background removal that calculates the foreground mask by performing a subtraction between the current frame and a background model, containing the static part of the scene or, more generally, everything that can be considered as background given the characteristics of the observed scene. An example is presented in Figure 2.5.

Since the video analysis process was a very time-consuming task which included performing subtasks for each video, such as homography, MOG 2 conversion, software calibration, processing the analysis itself, and refining and cleaning the exported data, and due to the fact of some sections have low pedestrian traffic volumes, the data collection from each street was limited to fifty crossing movements to avoid a large decompensation of the statistical weight of the variables related to the characteristics of the study sections. The total number of observations considered in this study was 459 pedestrian-vehicle encounters.

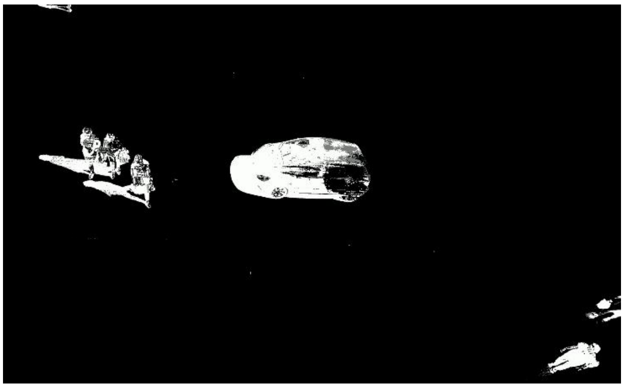
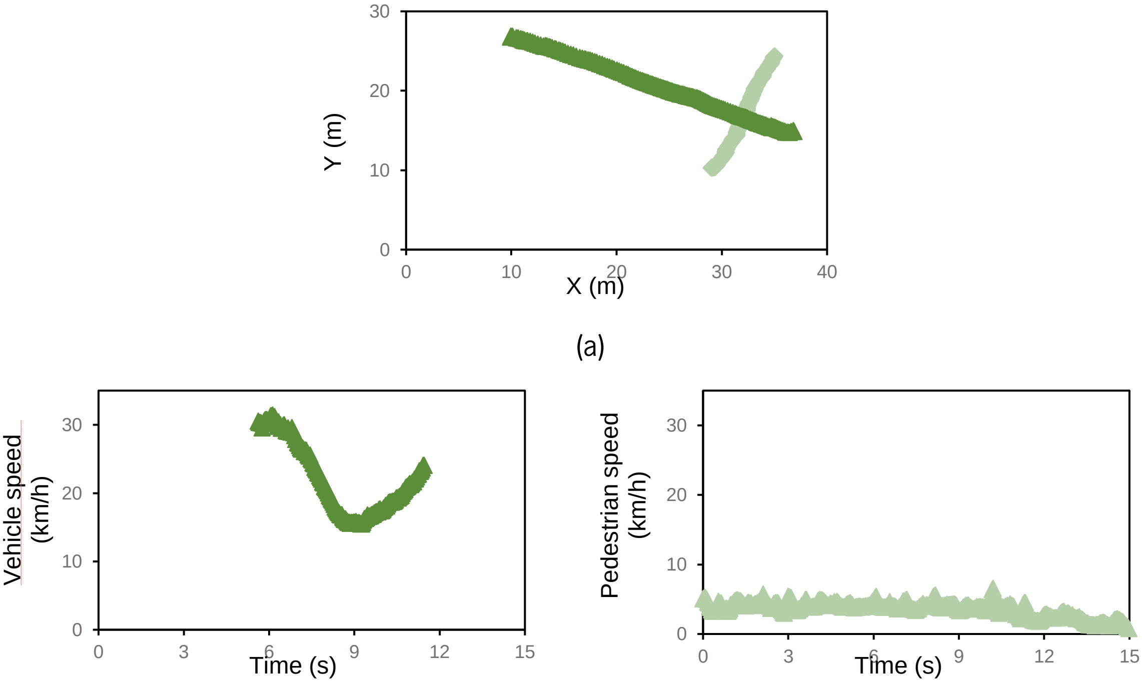


Figure 2.5 – Frame from a video converted to MOG 2.

An example of the data collected with the video analysis made through Traffic Intelligence is presented in Figure 2.6.



(a)

(b)

(c)

Figure 2.6 – Example of the data exported by Traffic Intelligence: a) pedestrian and vehicle trajectories along time; b) vehicle speed along time; c) pedestrian speed along time.

2.2.4 Linear mixed-effects model

The analysis of pedestrian crossing behaviour was carried out using two safety indicators as dependent variables, TTP and TTC_{min}. The first one allows to evaluate the severity of the encounter, *i.e.*, the possibility of an accident to occur, and the last one allows the assessment of the risk taken by pedestrians when they started the crossing task. PET was not used, since it requires consideration of the dimensions of the vehicles and pedestrians involved, which are not provided by the automated video analysis program. The impact of several variables related to the road and pedestrian infrastructure characteristics, the pedestrian demographic characteristics, and the pedestrian and motorized traffic characteristics on pedestrians' risk in crossing decision-making and during the effective crossing were then assessed considering both variables.

TTC_{min} is the minimum time remaining, during the encounter, before a collision occurs if road users, vehicle and pedestrian, continue with the speeds and trajectories that they had at the time for which the indicator was calculated (Archer, 2005; Hayward, 1972; Horst, 1990) (see Expression 2.1). For its determination, pedestrian and the vehicle's movement were considered during the time interval from the beginning of the crossing until the moment when one of them passed the intersection point between the trajectory of the vehicle and the pedestrian, *i.e.*, the point of conflict.

$$TTC_{min} = \min_{[0;\,t]} (\max (D_{vehicle\text{-}conflict\ point,\ i} / V_{vehicle,\ i};\ D_{pedestrian\text{-}conflict\ point,\ i} / V_{pedestrian,\ i}), \qquad (2.1)$$

$$i \in [0, ..., t]$$

Where:

- t is the encounter duration;
- $D_{vehicle\text{-}conflict\ point}$ is the distance, in m, from the centre of the vehicle's license plate, assumed as the possible point of impact, and the point of conflict;
- $V_{vehicle}$ is the vehicle speed, in m/s;
- $D_{pedestrian\text{-}conflict\ point}$ is the distance, in m, from the pedestrian to the point of conflict;
- $V_{pedestrian}$ is the pedestrian speed, in m/s.

TTP is a psychophysical indicator that consists of the time remaining until an object (vehicle) passes in front of an observer (pedestrian) if it continues with the speed and trajectory corresponding to the instant which the indicator is calculated (Hancock and Manser, 1998) (see Expression 2.2). In this case, this instant corresponded to the moment when the pedestrian crossing started. This indicator corresponds to TTZ, TG, and T2 used by some authors (Cavallo *et al.*, 2019; Laureshyn *et al.*, 2010; Lobjois and Cavallo, 2007; Várhelyi, 1998).

$$TTP = D_{\text{vehicle-conflict point}} \,/\, V_{\text{vehicle}} \tag{2.2}$$

Where:

- $D_{\text{vehicle-conflict point}}$ is the distance, in m, from the centre of the vehicle's license plate, assumed as the possible point of impact, to the point of conflict at the moment when pedestrian started to cross;
- V_{vehicle} is the vehicle speed, in m/s, at the moment when the pedestrian started to cross.

In some encounters, it was impossible to get the value referring to one of the two indicators due to the incapacity to detect all the vehicles' trajectories when pedestrians started the crossing. The final dataset thus contained, 285 observations for the TTP analysis and 459 for the TTC_{min}. In addition to the characteristics of the pedestrian and road infrastructure presented in Table 2.2 and Table 2.3, the pedestrian and motorized traffic volumes, shown in Table 2.4 and Table 2.5, and the demographic characteristics of pedestrians, age, and sex, both databases also include the average vehicle speed gathered during each encounter. As the number of observations among the groups compounding the variables was excessively unbalanced, the road directions (one or two directions), road pavement (asphalt concrete or cobble stones), and the number of lanes (two or four) were disregarded. A special relevance was given to vehicle approaching speed due to the TTP model results and the conclusions of some studies referred in the introductory section.

Linear mixed-effects models (LMM) were used to assess the influence of all the variables previously mentioned on TTP and TTC_{min}. LMM extend linear models by incorporating random effects, which can be regarded as additional error terms, to explain the correlation between observations within the same group. The LMM expresses for the i^{th} subject as (Pinheiro and Bates, 2006):

$$Y_i = X_i \beta + Z_i b_i + \varepsilon_i, \qquad i = 1, \ldots, n \qquad (2.3)$$

Where:

- $Y_i \in (Y_{i1} \ldots Y_{iTi})^T$ represents a vector (of size $T_i \times 1$) of continuous responses for the i^{th} subject;
- X_i is the known fixed-effects covariates matrix (of size $T_i \times p$);
- β is a vector (of size $p \times 1$) of unknown regression coefficients (or fixed-effects parameters);
- Z_i is the known random-effects covariates matrix (of size $T_i \times q$);
- b_i is a vector (of size $q \times 1$) of random-effects;
- ε_i represents an error vector (of size $T_i \times 1$) of n residuals associated with an observed response for the i^{th} subject.

Moreover:

$$b_i \sim N_q(0, D) \qquad (2.4)$$

$$\varepsilon_i \sim N_{Ti}(0, Ri) \qquad (2.5)$$

Where:

- D is the $q \times q$ covariance matrix for the random effects, and R_i is the $T_i \times T_i$ covariance matrix of the errors in group i;
- b_i e ε_i are independent for the same i^{th} subjects and of each other.

Following the methodology described on Pinheiro and Bates (2006), the significance of fixed effects' terms in the model was assessed by conditional F-tests using a sequential sum of squares. The Restricted Maximum Likelihood (REML) was used to estimate the parameters of the model. Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to choose the most appropriate structure for the covariance matrix of the errors, and the independent structure was selected (this structure assumes a homogeneous residual variance for all observations).

LMM is an appropriate technique for analysing nested structured data, such as the data presented in this study. The encounters are nested within streets, and repeated measures were collected on twelve different streets. The applicability of this technique was previously assessed before the construction of the models. When LMM was not applied, a simple linear regression model was considered. This work's modelling approach followed the backward deletion method, which consisted of iteratively removing the statistically non-significant variable with the highest p-value. The final model for each response variable, namely TTP and TTC_{min}, presents the explanatory variables that were statistically significant to a level of 5 %. Before the first iteration of the model's construction task, a Pearson correlation analysis was performed to examine whether some explanatory variable was highly correlated with the response variable. All statistical analyses were performed using the R statistical software (R Core Team, 2020).

2.3. Results

2.3.1 Time-to-passage

An one-way ANOVA revealed statistically significant differences in TTP between the streets, F(11, 273) = 2.08, p = 0.02. Analysing Figure 2.7, it is possible to note that the registered TTP not only had considerable variations between streets, with the higher and lower mean values having been registered to the TP (m = 4.59 s; sd = 1.93 s) and GNM (m = 2.90 s; sd = 1.06 s) streets, respectively, but also within the street itself, particularly in NSC (m = 3.58 s; sd = 2.01 s), TP, and CL (m = 3.91 s; sd = 1.92 s).

The statistical summary of the quantitative variables used in the modelling analysis of TTP presented in Table 2.7 shows that, in general, the TTP ranged from 1.02 to 8.92 s (m = 3.69 s; sd = 1.73 s). It is also possible to notice that the difference between the maximum value of TTP (Max) and the value of the third quartile (Q_3) is bigger than the difference between the value of the first quartile (Q_1) and its minimum value

(Min), indicating a positively skewed distribution of the TTP. This situation was expected because TTP is a temporal indicator, limited to positive values, which forces a boundary in the zero value. This feature could cause the violation of one of the assumptions that must be met for applying the LMM, which is the normality of the distribution of residuals. A new variable was created based on its natural logarithm (logTTP) to lead with this instead of considering the TTP as the model's dependent variable.

The mean speed of the vehicles throughout the encounters ranged from 2.13 to 50.69 km/h (m = 17.88 km/h; sd = 9.22 km/h). In average terms, lower vehicle approaching speeds were registered in CJ (m = 7.96 km/h; sd = 2.76 km/h) and TP (m = 10.70 km/h; sd = 5.03 km/h) streets. In turn, SG (m = 27.20 km/h; sd = 11.60 km/h) and CL (m = 23.40 km/h; sd = 9.48 km/h) were the streets with the highest recorded values.

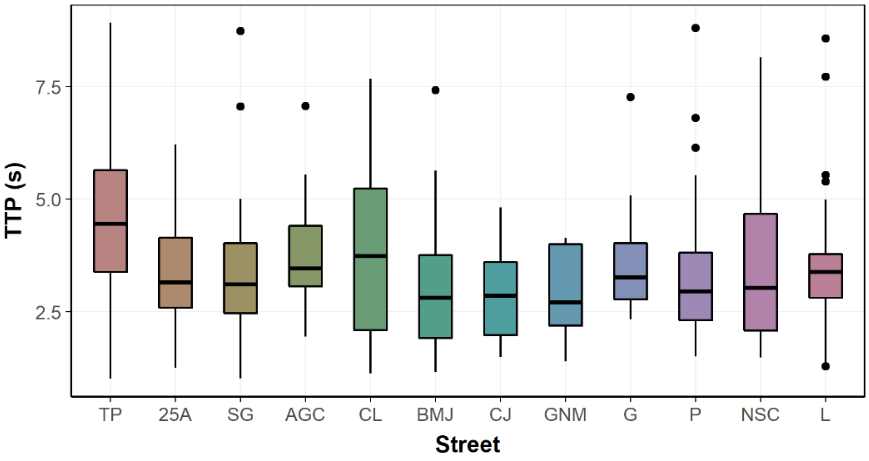


Figure 2.7 – Boxplot of TTP as a function of street.

Table 2.6 presents the statistical summary of the quantitative variables used in the modelling analysis of TTP. Regarding the pedestrians' age, most of the sample comprises data gathered from road crossings done by adult pedestrians, *i.e.*, those belonging to the [20 – 40[and [40 – 60[age groups. Despite the sample's balance, more crossings were observed of female (55.09 %) than male pedestrians. 70.88 % of all the considered pedestrian-vehicle encounters took place on a crosswalk located on a collector road. Regarding the remaining variables, both those related to the road and pedestrian infrastructure characteristics and traffic volumes, the minimum and maximum values presented in Table 2.7 are in line with those previously presented in Table 2.2, Table 2.3, Table 2.4, and Table 2.5, contrary to the other values presented (Q_1, Q3, Median, Mean, SD and Coefficient of variation) since they depended on the number of pedestrian-vehicle encounters recorded in each street.

Table 2.6 – Frequencies of the qualitative variables considered to model the TTP.

Variable	**Abbreviation**	**Group**	**Absolute Frequency**	**Relative Frequency (%)**
Pedestrian's age	PartAge	< 20	30	10.53
		[20 – 40[	135	47.37
		[40 – 60[	74	25.96
		> 60	46	16.14
Pedestrian's sex	PartGen	Female	157	55.09
		Male	128	44.91
Road classification	Road_class	Collector	202	70.88
		Local	83	29.12

The Pearson correlation analysis revealed that the mean speed of the vehicles along the encounters was the variable with the highest correlation with TTP (ρ = - 0.22), even though this was a low value ($|\rho| < 0.30$) (Hinkle *et al.*, 2003).

Following, as a first step, the null model, *i.e.*, the model with no covariates, was fitted (Expression 2.6). The null model is useful for deciding whether a random-effects model might be appropriate for the data. Since $\sigma_P^2 = 0.0085$ and $\sigma_\varepsilon^2 = 0.2178$, only 3.75 % (0.0085 / (0.2178 + 0.0085)) of the data variation is explained by allowing the intercept to vary across the streets, indicating that unobserved heterogeneity of logTTP among the streets may not be captured by using a random-intercept model. Thus, a simple linear regression was fitted to identify the variables with a significant effect on logTTP. The first iteration of modelling task considered all the variables previously described (see Expression 2.7).

$$\text{logTTP}_{s,i} = \beta_{0,i} + b_{0,i} + \varepsilon_{s,i}, \tag{2.6}$$

$b_{0,i} \sim N(0, \sigma_P^2)$, $\varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2)$, s = 1st, ..., 12th street, and i = 1st, ..., 285th observation

Table 2.7 – Statistical summary of the quantitative variables considered to model the TTP.

Variable	Abbreviation	Unit	Min	Q_1	Median	Mean	Q_3	Max	SD	Coef. of Variation
Time-to-passage	TTP	s	1.02	2.45	3.35	3.69	4.54	8.92	1.73	0.47
Logarithm of TTP	logTTP	s	0.01	0.90	1.21	1.20	1.51	2.19	0.48	0.40
Vehicles' mean speed	CarSpeed_mean	km/h	2.13	10.47	16.29	17.88	23.46	50.69	9.22	0.52
Length of the crosswalk	Cross_length	m	5.21	7.13	7.73	8.47	9.96	13.80	1.88	0.22
Average width of the lanes	Lane_width	m	2.56	3.00	3.32	3.28	3.57	3.87	0.36	0.11
Width of the street to park	Parking_width	m	0	0	2.34	3.85	5.17	10.12	3.42	0.89
Average width of the sidewalk	Sidewalk_width	m	1.32	1.67	2.96	3.35	4.17	6.57	1.81	0.54
Width of the crosswalk	Cross_width	m	2.64	3.04	4.05	3.95	4.48	5.35	0.84	0.21
Distance to a bus stop	BusStop_dist	m	15.30	34.20	46.10	62.50	104.30	195.20	42.17	0.67
Motorized traffic volume	Veh_vol	veh/h	108	579	595	702.90	784	1286	300.41	0.43
Pedestrian traffic volume	Ped_vol	ped/h	31	65	85	187.30	276	631	170.16	0.91

$$\log TTP_i = \beta_0 + \beta_1 Cross\_length + \beta_2 Lane\_width + \beta_3 Parking\_width + \beta_4 Sidewalk\_width + \beta_5 Cross\_width + \beta_6 BusStop\_dist + \beta_7 Road\_class + \beta_8 Veh\_vol + \beta_9 Ped\_vol + \beta_{10} CarSpeed\_mean + \beta_{11} PartAge + \beta_{12} PartGen + \varepsilon_i, \quad (2.7)$$

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2),\ i = 1^{st}, \ldots, 285^{th} \text{ observation}$$

The results obtained for the first iteration of the TTP model are presented in Table 2.8. Among all the considered variables, only the vehicles' mean speed was found to be statistically significant ($\beta = -0.0122$, $p < 0.01$). Although they are not the final results of the TTP model, it is shown that the higher the mean approaching speed of the vehicles, the lower the logTTP, and thus the riskier the crossing decision made.

Table 2.8 – Results of the 1st iteration of the TTP model.

	β	**Std. Error**	**p-value**
Intercept	0.4257	1.3694	0.76
Cross_length	0.0123	0.0425	0.77
Lane_width	0.3061	0.3375	0.37
Parking_width	0.0380	0.0256	0.14
Sidewalk_width	- 0.0251	0.0214	0.24
Cross_width	- 0.0192	0.0672	0.77
BusStop_dist	- 0.0008	0.0008	0.34
Veh_vol	- 0.0002	0.0003	0.54
Ped_vol	0.0001	0.0004	0.79
CarSpeed_mean	- 0.0120	0.0037	< 0.01
Road_class (ref. Arterial)			
Local	0.1060	0.2661	0.69
PartAge (ref. [20 – 40[)			
< 20	0.0599	0.0700	0.39
[40 – 60[	- 0.1376	0.1010	0.17
> 60	0.0390	0.0831	0.64
PartGen (ref. Female)			
Male	- 0.0230	0.0577	0.69

ε	0.46
R^2	0.10

The iterative process continued with the removal of the Ped_vol variable (p = 0.79), and so on, until the last (12th) iteration, where only the CarSpeed_mean and Parking_width variables remained (Expression 2.8). The results of the final iteration of the TTP model are presented in Table 2.9.

$$\text{logTTP}_i = 1.2884 + 0.0218\,\text{Parking\_width} - 0.0099\text{CarSpeed\_mean} + \varepsilon_i, \qquad (2.8)$$

$$\varepsilon_{s,i} \sim N\,(0, \sigma_{\varepsilon}^2),\ i = 1^{st}, \ldots, 285^{th}\ \text{observation}$$

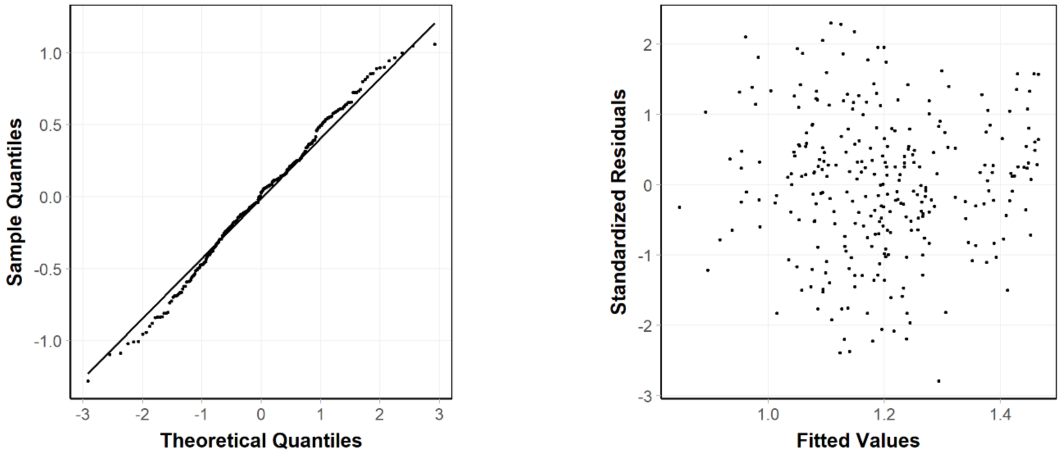
Table 2.9 – Results of the final iteration of the TTP model.

	β	**Std. Error**	**p-value**
Intercept	1.2884	0.0749	< 0.01
Parking_width	0.0218	0.0082	< 0.01
CarSpeed_mean	- 0.0099	0.0031	< 0.01
ε		0.46	
R^2		0.08	

The low value of the coefficient of determination (R^2 = 0.08) shows that the linear regression model is not the best one to explain how the logTTP varies with the considered variables. However, this analysis aimed to identify the variables with a significant effect on logTTP and not explain the variation of the logTTP.

The effect of the vehicle's mean speed on logTTP (β = - 0.0099) is bigger than that verified in the first iteration of the modelling process. The transversal width of the street intended for parking spaces had a significant and positive effect on logTTP (β = 0.0218) and, thus, on pedestrian safety. The bigger the transversal width of the street occupied by parking spaces, the bigger the logTTP.

Furthermore, based on the Normal quantile-quantile (Q-Q) plot, it was assumed that no significant deviations from the normality existed (Figure 2.8(a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 2.8(b)). The residuals appear to be homogeneously distributed.



(a) (b)

Figure 2.8 – Verification of the assumptions for the TTP model: (a) Q-Q plot; (b) Standardized residual versus fitted values.

Since it was a variable with significant importance in pedestrian crossing decision-making, the construction of a model to analyse which variables related to the characteristics of the road and pedestrian infrastructure and traffic characteristics affect the approaching vehicles' mean speed was considered. Following this approach, the influence of those variables on crossing decision-making and, consequently, on pedestrians' safety was assessed carrying out the LMM technique. The natural logarithm of CarSpeed_mean was considered the dependent variable for the same reason the logTTP was considered for the TTP modelling. The Pearson correlation analysis revealed that the crosswalk's length was the variable with the highest correlation with the mean speed of the vehicles (ρ = 0.29 Still, it was also a low correlation ($|\rho|$ < 0.30). The null model of the natural logarithm of CarSpeed_mean was then fitted (Expression 2.9).

$$\text{logCarSpeed\_mean}_{s,i} = \beta_{0,i} + b_{0,i} + \varepsilon_{s,i}, \qquad (2.9)$$

$b_{0,i} \sim N\,(0, \sigma_P^2)$, $\varepsilon_{s,i} \sim N\,(0, \sigma_\varepsilon^2)$, s = 1sr, ..., 12th street, and i = 1st, ..., 285th observation

Since $\sigma_P^2 = 0.1171$ and $\sigma_\varepsilon^2 = 0.1704$, 40.72 % (0.1171 / (0.1704 + 0.1171)) of the data variation is explained by allowing the intercept to vary across the streets, indicating that unobserved heterogeneity of logCarSpeed_mean among the streets is better captured using a random-intercept model. The first iteration of the modelling task considered all the variables previously described (see Expression 2.10).

$$\begin{aligned} \text{logCarSpeed\_mean}_{s,i} = {} & \beta_{0,i} + \beta_1\,\text{Cross\_length}_{s,I} + \beta_2\,\text{Lane\_width}_{s,I} + \beta_3\,\text{Parking\_width}_{s,I} + \\ & \beta_4\,\text{Sidewalk\_width}_{s,I} + \beta_5\,\text{Cross\_width}_{s,i} + \beta_6\,\text{BusStop\_dist}_{s,I} + \\ & \beta_7\,\text{Road\_class}_{s,I} + \beta_8\,\text{Veh\_vol}_{s,I} + \beta_9\,\text{Ped\_vol}_{s,I} + b_{0,i} + \varepsilon_{s,i}, \\ & b_{0,i} \sim N(0, \sigma_P^2),\ \varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2),\ s = 1^{st}, \ldots, 12^{th} \text{ street, and } i = 1^{st}, \ldots, \\ & 285^{th} \text{ observation} \end{aligned} \tag{2.10}$$

The results obtained for the first iteration of the CarSpeed_mean model are presented in Table 2.10. None of the considered variables were statistically significant in the first iteration of the modelling approach.

Table 2.10 – Results of the 1st iteration of the CarSpeed_mean model.

	β	**Std. Error**	**p-value**
Intercept	- 1.6054	1.5631	0.31
Cross_length	0.1819	0.0471	0.06
Lane_width	0.9731	0.3848	0.13
Parking_width	0.0076	0.0294	0.82
Sidewalk_width	- 0.0335	0.0299	0.38
Cross_width	0.0195	0.0894	0.85
BusStop_dist	- 0.0036	0.0010	0.07
Veh_vol	0.0000	0.0003	0.98
Ped_vol	- 0.0016	0.0006	0.10
Road_class (ref. Arterial)			
Local	0.5243	0.3185	0.24

σ_P^2	0.0103
σ_ε^2	0.1702

The iterative process continued with the removal of the Veh_vol variable (p = 0.98). The process stopped in the 7th iteration, where only the Cross_length, Lane_width, BusStop_dist, and Ped_vol variables were considered (Expression 2.11).

$$\text{logCarSpeed\_mean}_{s,i} = 0.7086 + 0.1140\,\text{Cross\_length}_{s,i} + 0.4716\,\text{Lane\_width}_{s,i} - 0.0036\,\text{BusStop\_dist}_{s,i} - 0.0012\,\text{Ped\_vol}_{s,i} + b_{0,i} + \varepsilon_{s,i}, \quad (2.11)$$

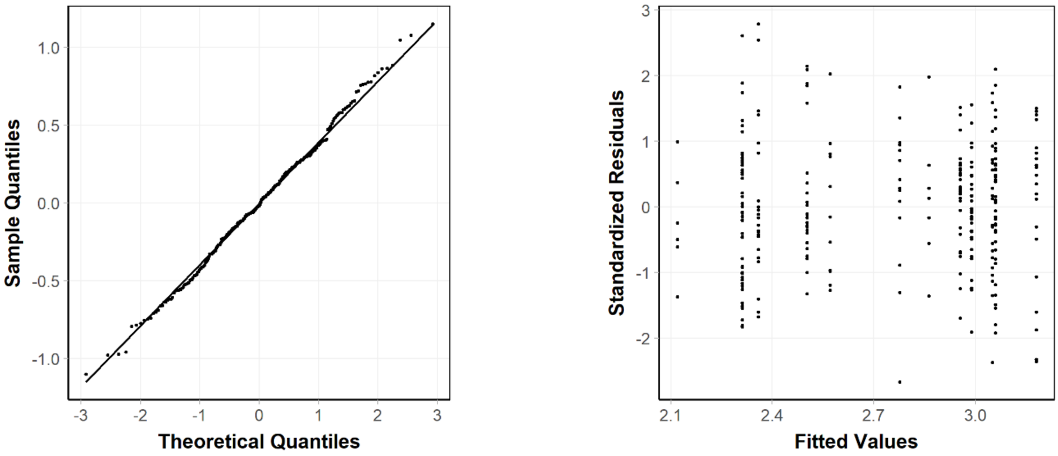
$b_{0,i} \sim N(0, \sigma_P^2)$, $\varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2)$, s = 1sr, ..., 12th street, and i = 1st, ..., 285th observation

The results of the final iteration of the CarSpeed_mean model are presented in Table 2.11.

According to the results of the CarSpeed_mean model, the increasing in Cross_length ($\beta = 0.1140$, $p < 0.01$) and Lane_width ($\beta = 0.4716$, $p < 0.01$) is associated with the increasing of the mean speed of the approaching vehicles. Wider lanes and larger crosswalks imply wider roads. On the other hand, the BusStop_dist ($\beta = -0.0036$, $p < 0.01$) and Ped_vol ($\beta = -0.0012$, $p < 0.01$) were revealed as variables that can attenuate the speed of the vehicles.

Table 2.11 – Results of the final iteration of the CarSpeed_mean model.

	β	**Std. Error**	**p-value**
Intercept	0.7086	0.4346	0.10
Cross_length	0.1140	0.0204	< 0.01
Lane_width	0.4716	0.1183	< 0.01
BusStop_dist	- 0.0036	0.0010	< 0.01
Ped_vol	- 0.0012	0.0002	< 0.01
σ_P^2	0.0119		
σ_ε^2	0.1700		



(a) (b)

Figure 2.9 – Verification of the assumptions for the CarSpeed_mean model: (a) Q-Q plot; (b) Standardized residual versus fitted values.

No significant deviations from the normality assumption were found in the CarSpeed_mean model (Figure 2.9(a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 2.9(b)). The residuals appear to be homogeneously distributed, which indicates a good fit of the model.

2.3.2 Minimum time-to-collision

The one-way ANOVA run to analyse TTC_{min} revealed statistically significant differences between the streets, $F(11, 447) = 3.23$, $p < 0.01$. Analysing the Figure 2.10, it is possible to note that, such as TTP, the registered TTC_{min} not only had considerable variations between streets, with the higher and lower mean values having been registered to the TP (m = 3.35 s; sd = 0.98 s) and P (m = 2.50 s; sd = 0.89 s) streets, respectively, but also within the street itself, particularly in AGC (m = 2.87 s; sd = 1.45 s), SG (m = 2.75 s; sd = 1.12 s), and NSC (m = 3.25 s; sd = 1.06 s).

The mean speed of the vehicles throughout the encounters ranged from 2.13 to 80.57 km/h (m = 19.50 km/h; sd = 11.02 km/h). In average terms, lower vehicle approaching speeds were registered in CJ (m = 11.40 km/h; sd = 5.52 km/h) and TP (m = 11.80 km/h; sd = 5.09 km/h) streets. In turn, BMJ (m = 28.60 km/h; sd = 16.50 km/h) and CL (m = 23.60 km/h; sd = 9.32 km/h) were the streets with the highest recorded values.

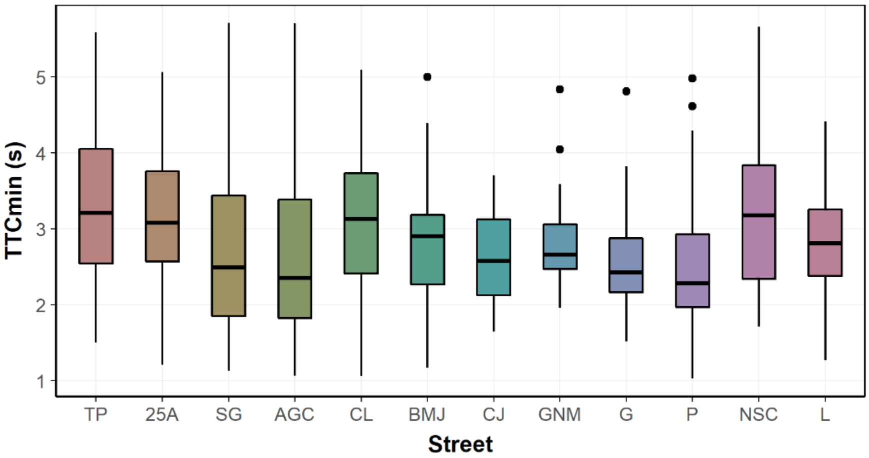


Figure 2.10 – Boxplot of TTC_{min} as a function of street.

Table 2.12 presents the statistical summary of the quantitative variables used in the modelling analysis of TTC_{min}. Regarding the pedestrians' age, most of the sample (72.42 %) is composed of data gathered from road crossings done by adult pedestrians, *i.e.*, those belonging to the [20 – 40[and [40 – 60[ages groups. Concerning pedestrians' sex, the sample is balanced, existing few more records of crossings performed by females (55.77 %) than male pedestrians. On the other hand, 65.36 % of all the considered pedestrian-vehicle encounters took place on a crosswalk located on a collector road. About the remaining variables, both those related to the road and pedestrian infrastructure characteristics and traffic volumes, such as for TTP analysis, the minimum and maximum values presented in Table 2.13 are in line with those previously presented in Table 2.2, Table 2.3, Table 2.4, and Table 2.5, with the exception for Q_1, Q_3, Median, Mean, SD, and Coefficient of variation values.

Table 2.12 – Frequencies of the qualitative variables considered to model the TTC_{min}.

Variable	Abbreviation	Group	Absolute Frequency	Relative Frequency (%)
Pedestrian's age	PartAge	< 20	50	10.89
		[20 - 40[	223	48.58
		[40 - 60[	114	24.84
		> 60	72	15.69
Pedestrian's sex	PartGen	Female	256	55.77
		Male	203	44.23
Road classification	Road_class	Collector	300	65.36
		Local	159	34.64

Table 2.13 – Statistical summary of the quantitative variables considered to model the TTC_{min}.

Variable	**Abbreviation**	**Unit**	**Min**	**Q_1**	**Median**	**Mean**	**Q_3**	**Max**	**SD**	**Coef. of Variation**
Time-to-passage	TTC_{min}	s	1.03	2.27	2.86	2.95	3.53	5.71	0.97	0.33
Logarithm of TTP	$logTTC_{min}$	s	0.03	0.82	1.05	1.03	1.26	1.74	0.34	0.33
Vehicles' mean speed	CarSpeed_mean	km/h	2.13	10.89	17.87	19.50	25.44	80.57	11.02	0.57
Length of the crosswalk	Cross_length	m	5.21	7.13	7.85	8.72	9.96	13.80	2.04	0.23
Average width of the lanes	Lane_width	m	2.56	3.00	3.26	3.23	3.57	3.87	0.35	0.11
Width of the street to park	Parking_width	m	0	0	4.23	3.68	5.17	10.12	3.26	0.89
Average width of the sidewalk	Sidewalk_width	m	1.32	1.67	2.96	3.42	4.17	6.57	1.82	0.53
Width of the crosswalk	Cross_width	m	2.64	3.29	4.05	3.99	4.48	5.35	0.86	0.21
Distance to a bus stop	BusStop_dist	m	15.30	22.40	46.10	58.11	87.60	195.20	40.56	0.70
Motorized traffic volume	Veh_vol	veh/h	108	528	595	674.50	760	1286	285.67	0.42
Pedestrian traffic volume	Ped_vol	ped/h	31	65	85	205.90	276	631	182.27	0.89

The statistical summary of the quantitative variables used in the modelling analysis of TTC_{min} presented in Table 2.13 shows that, in general, the TTC_{min} ranged from 1.03 to 5.71 s (m = 2.95 s; sd = 0.97 s). Such as TTP, although it is not so easy to notice, the difference between the maximum value of TTC_{min} (Max) and the value of the third quartile (Q_3) is bigger than the difference between the value of the first quartile (Q_1) and its minimum value (Min), indicating a positively skewed distribution of the TTC_{min}. In this way and for the same justification used for TTP, instead of considering the TTC_{min} as the model's dependent variable, a new variable was created based on its natural logarithm – $logTTC_{min}$.

The Pearson correlation analysis revealed that the pedestrian traffic volume was the variable with the highest correlation with TTC_{min} ($\rho = 0.18$), although it was still a low value ($|\rho| < 0.30$). The null model was firstly fitted (Expression 2.12), but, such as in the TTP model, the results showed that the unobserved heterogeneity of $logTTC_{min}$ among the streets may not be captured using the LMM technique.

$$logTTCmin_{s,i} = \beta_{0,i} + b_{0,i} + \varepsilon_{s,i}, \tag{2.12}$$

$b_{0,i} \sim N(0, \sigma_P^2)$, $\varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2)$, s = 1st, ..., 12th street, and i = 1st, ..., 459th observation

The first iteration of the process was then to fit a simple linear regression to identify the variables with a significant effect on $logTTC_{min}$. The results obtained for the first iteration of the TTC_{min} model are presented in Table 2.14. None of the considered variables were statistically significant in this first iteration.

The iterative process continued with the removal of the Parking_width variable (p = 0.87). The 11th iteration was the last one. It only considered the Veh_vol, Ped_vol, and Cross_width variables (Expression 2.14). The results of the final iteration of the TTC_{min} model are presented in Table 2.15.

$$\log TTC_{min,s,i} = 1.0370 - 0.0591\ Cross\_width_{s,i} + 0.0002\ Veh\_vol_{s,i} + 0.0004\ Ped\_vol_{s,i} + \varepsilon_{s,i}, \quad (2.13)$$

$$\varepsilon_{s,i} \sim N(0, \sigma_{\varepsilon}^2),\ i = 1^{st}, \ldots, 459^{th} \text{ observation}$$

Table 2.14 – Results of the 1st iteration of the TTC_{min} model.

	β	**Std. Error**	**p-value**
Intercept	2.1006	0.7204	< 0.01
Cross_length	- 0.0269	0.0218	0.217
Lane_width	- 0.1943	0.1780	0.276
Parking_width	0.0023	0.0136	0.866
Sidewalk_width	0.0110	0.0125	0.378
Cross_width	- 0.0949	0.0349	< 0.01
BusStop_dist	- 0.0002	0.0005	0.597
Veh_vol	0.0002	0.0001	0.242
Ped_vol	0.0006	0.0002	< 0.01
CarSpeed_mean	- 0.0013	0.0016	0.424
Road_class (ref. Arterial)			
Local	- 0.2176	0.1414	0.125
PartAge (ref. [20 – 40[)			
< 20	- 0.0025	0.0397	0.950
[40 – 60[	0.0369	0.0558	0.509
> 60	0.0085	0.0465	0.855
PartGen (ref. Female)			
Male	-0.0223	0.0323	0.489

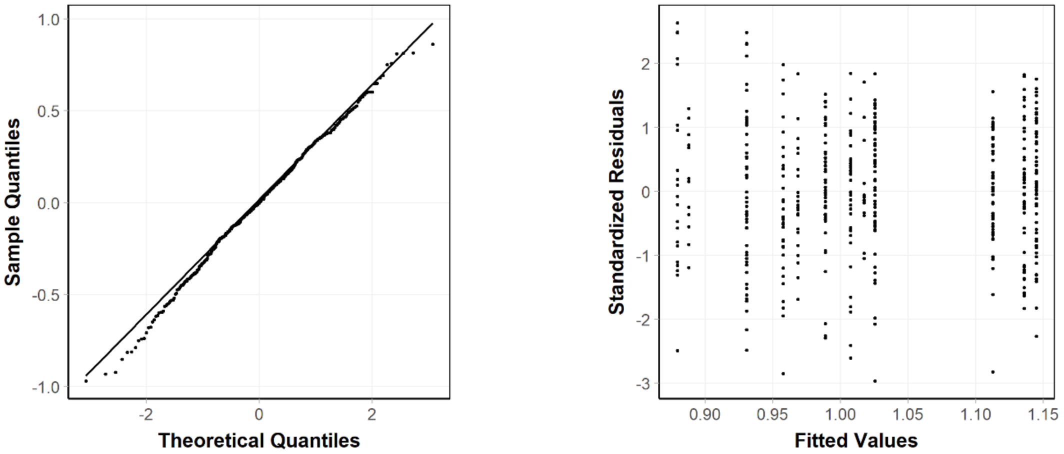
ε	0.34
R^2	0.08

Like in the TTP analysis, the low value of the coefficient of determination ($R^2 = 0.06$) shows that the linear regression model is not the best technique to explain the variation of $\log TTC_{min}$. However, this analysis aimed primarily to identify the variables with a significant effect. In this way, the increasing of the crosswalk width leads to a decreasing of the $\log TTC_{min}$ values ($\beta = -0.0591$, $p < 0.01$). The increase of both the motorized ($\beta = 0.0002$, $p < 0.01$) and pedestrian traffic ($\beta = 0.0004$, $p < 0.01$) volumes leads to higher $\log TTC_{min}$ values.

Table 2.15 – Results of the final iteration of the TTC_{min} model.

	β	**Std. Error**	**p-value**
Intercept	1.0370	0.0775	< 0.01
Cross_width	-0.0591	0.0226	< 0.01
Veh_vol	0.0002	0.0001	< 0.01
Ped_vol	0.0004	0.0001	< 0.01
ε		0.33	
R^2		0.06	

The Normal quantile-quantile (Q-Q) plot shows that there are no significant deviations from the normality assumption (Figure 2.11(a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 2.11(b)).



(a) (b)

Figure 2.11 – Verification of the assumptions for the TTC_{min} model: (a) Q-Q plot; (b) Standardized residual versus fitted values.

2.4. Discussion

The analysis carried out in this chapter was mainly divided into two distinct parts. The impact of variables belonging to three different groups, namely the characteristics of the built environment, the characteristics of pedestrian and motorized traffic, and the demographic characteristics of pedestrians, was first assessed in terms of pedestrian crossing decision-making through TTP and, subsequently, in terms of the severity of the encounter between pedestrians and vehicles through TTC_{min} on the considered crosswalks.

As referred in the introductory section of this chapter, some authors argue that vehicle approaching speed has the most important role in pedestrian crossing decision-making (Granié *et al.*, 2014; Sucha *et al.*, 2017), and for others, it is the single variable appropriate to describe pedestrian safety and feeling of safety (Várhelyi, 1998). The results obtained in the analysis of TTP showed that the vehicle approaching speed has, in fact, a significant impact on pedestrian crossing decision. This is in line with Liu and Tung (2014) conclusions, which states that higher speeds can precipitate riskier crossing decisions, leading pedestrians to accept shorter time gaps and thus putting their safety and integrity at risk.

Vehicle speed was not, however, the only significant variable. The transversal width of the street occupied by demarked parking places has played a role in defining TTP. According to Granié *et al.* (2014), the lack of parking places can induce a sensation of discomfort and lack of security in pedestrians when they decide and cross the road because it leads them to infer the existence of low volumes of pedestrian and motorized traffic, which, consequently, implies the practice of higher speeds by the drivers. Indeed, the TTP model results showed a significant positive effect of the street's parking width, which means that the greater the width of the street used for parking places, the safer the crossing decision. The explanation for that could be based on two distinct points or on the combination of both: (i) the practice of lower speeds by drivers due to the parking, agreeing, in part, with the justification of Granié *et al.* (2014); or (ii) a greater level of caution and prudence felt by pedestrians in crossing judgement motivated by the parked vehicles which act as masks of the approaching vehicles.

Since it was a variable with significant influence on pedestrians' crossing decision, it was decided to evaluate which variables related to the characteristics of the road and pedestrian infrastructure and the characteristics of traffic have significant effects on the vehicles approaching speed. The results of this part of the work support the view that larger roads, with wider lanes and longer crosswalks, provide favourable conditions for the practice of higher speeds by drivers (Sucha *et al.*, 2017; Turner *et al.*, 2006; Zegeer *et al.*, 2006). Furthermore, they are also in line with the results of Leden (2002), which points that bigger pedestrian traffic volumes lead to lower approaching speeds of vehicles. This can also be explained by the same justification presented by the author, who refers that the decreasing of a vehicle approaching speed is due to the greater driver alertness about the presence of pedestrians.

The distance to the closest bus stop was the other variable that significantly affected vehicles' approaching speed. The greater the distance from the crosswalk to a bus stop, the lower the vehicles' mean approaching speed. The existence of bus stops near the crosswalk can affect the detection of pedestrians by drivers. They can be masked by buses, by other pedestrians, and even by the bus stop itself. Indeed, the results seem to indicate that it is easier for drivers to detect pedestrians approaching the crosswalk and adjust the vehicle speed when their sight view is clean.

The results of the model of approaching speed have also allowed clarifying the role of the width of the street to park in pedestrians' crossing decision-making. This variable had no significant effect on the vehicles approaching speed, which indicates that, it only affects the pedestrians' decision-making. A possible explanation for this is the greater feeling of caution and prudence in crossing judgement task that this characteristic can promote and not a possible repercussion of the lower speeds practiced by drivers due to the parking manoeuvres, such as suggested by Granié *et al.* (2014).

Regarding the severity of the pedestrian-vehicle encounter, the results of the model of TTC_{min} showed that only three of all the considered variables had a significant effect: the width of the crosswalk, the pedestrian traffic volume, and motorized traffic volume. If the crosswalk is wider, it should be easier for drivers to detect it and thus start to slow down the vehicle at a bigger distance, leading to longer TTC_{min} and safer crossings or encounters. However, this was not observed. The effect of the width of the crosswalk on TTC_{min} was in fact opposite to the expected. One explanation for this may be a greater sense of comfort and safety felt by pedestrians, leading to an excessive level of confidence during the crossing, which may jeopardize their safety.

In addition to having an impact on the approaching speed of the vehicles which influenced the pedestrians' crossing decision, the pedestrian traffic volume also has a positive effect on TTC_{min}. As previously explained, this effect can be explained by the increase of the detectability of pedestrians by drivers (Leden (2002). On the other hand, the effect of motorized traffic volume was in the opposite direction of conclusions of Leden (2002). In this case, the higher the motorized traffic volume, the safer the pedestrian-vehicle encounters. As well as higher pedestrian traffic volumes can increase the drivers' alertness, greater motorized traffic volumes can affect pedestrian's caution. Besides, depending on road capacity, higher motorized traffic volumes can make high speeds impossible to be practiced by drivers.

The variables related to the pedestrian characteristics, namely their age and sex, did not show an influence on pedestrian crossing safety, neither on the crossing decision making nor on the severity of conflict in the observed cases. This is in line with the conclusion of the study of Papadimitriou *et al.* (2016b) and contrary to what was expected and verified in other studies (Bernhoft and Carstensen, 2008; Ezzati Amini *et al.*, 2019; Hamed, 2001; Holland and Hill, 2007; Johansson *et al.*, 2004; Moyano Díaz, 2002; Rosenbloom *et al.*, 2008).

In general, the results of the three models show the biggest limitation of the study presented on this chapter: the observed TTP and TTC_{min} are not linearly explained by a simple regression. However, this part of the work aimed to identify the variables related with road and pedestrian infrastructure, pedestrians' demographics, and pedestrian and motorized traffic characteristics on pedestrians' decision and interaction with motorized vehicles when crossing the road. In order to assess and compare the effect of the different variables on the considered indicators, other modelling techniques should be considered taking into account the statistical characteristics of the data sample.

Future work should complement this approach with data gathered in the same streets in to increase the dimension of the sample and to give more robustness to the results. It would be also interesting to consider other different streets of the same cities or even other cities in the study to assess the impact of sociocultural characteristics and city dimension on pedestrian crossing decision and safety and to increase the variability of the road and pedestrian infrastructure characteristics, allowing for the consideration of other variables which were not considered, such as the number of lanes, the land use, the road pavement, etc.

2.5. Conclusions

The study presented in this chapter aimed to analyse the importance of factors linked to pedestrians' demographics, road and pedestrian infrastructure, and traffic characteristics on pedestrian crossing safety, by assessing its influence on pedestrian crossing decision-making and the severity of pedestrian-vehicle encounters. Video recordings were performed in twelve different crosswalks located in two different Portuguese cities, Guimarães and Braga. The trajectories and speeds of pedestrians and vehicles were collected using automated video analysis software, and, from these data, indicators such as TTP and TTC_{min} were calculated.

The process of video recording and analysis was a long one which involved many hours of human and computational analysis. In addition, variables such as the pedestrians' age and sex were not always easy to estimate, since, in order to significantly cover an area surrounding the crosswalk, the camera always had to be placed at a considerable distance and height. However, only in this way was it possible to extract a big and useful amount of data on pedestrians and vehicles.

The models constructed to analyse the gathered data seem to support the view that factors such as speed and width of the crosswalk had a direct negative effect on pedestrian crossing safety, with higher values of the first one leading pedestrian to accept lower TTP to cross and higher values of the second one leading to the registration of minors TTC_{min} values. In contrast, the street's width intended for parking places, due to the influence on the crossing decision, and the volumes of pedestrian and motorized traffic, due to the severity of the encounter, revealed a favourable effect on pedestrian safety. The lane width, the length of the crosswalk, the distance to the nearest bus stop, and again the pedestrian traffic volume significantly influenced the approaching speeds of vehicles and, thus, the safety of the most vulnerable road users, given that: the higher the first two, the higher the speeds practiced by drivers; the higher the remaining two, the lower the speeds practiced by drivers.

3. THE INFLUENCE OF NOISE EMITTED BY VEHICLES ON PEDESTRIAN CROSSING DECISION-MAKING

3.1. Introduction

Cars are inherently noisy machines. This noise may come from its internal components, such as the engine, exhaust, and, to a lesser extent, fan and structural vibration, and from external sources, namely tire–road contact and air turbulence. The former are the primary source of noise at lower speeds, which are usually observed in urban contexts. The latter become relevant at higher speeds, more often seen on rural roads or highways. Despite several technical developments on noise attenuation technology both in and outside the vehicle, motorized vehicles are currently one of the most important sources of noise pollution (Stelling-Konczak *et al.*, 2015). Noise disturbs sleep, interferes in complex task performance such as school performance, modifies social behaviour, and causes emotional annoyance (Freitas *et al.*, 2012; Mendonça *et al.*, 2013; Soares *et al.*, 2017; Stansfeld and Matheson, 2003). This problem is well acknowledged by public authorities, vehicle manufacturers, and road industries that have continuously tried to find ways to eliminate or at least attenuate the noise emissions (Freitas *et al.*, 2012; Mendonça *et al.*, 2013; Soares *et al.*, 2017; Stansfeld and Matheson, 2003; Stelling-Konczak *et al.*, 2015).

While vehicle noise is often regarded as an undesirable sub-product of transportation, it also has an important role in the interaction between vehicles and other road users, most notably, pedestrians and cyclists. Particularly in urban areas, vehicular noise often acts as a cue for vulnerable road users, improving their perception of speed and distance and calling their attention to approaching traffic. This dual nature of vehicular noise in relation to other agents raises some concerns regarding the increasing introduction of hybrid/electric vehicles that are considerably quieter than their combustion counterparts. On the one hand, hybrid and electrical vehicles emit less or no engine noise. At speeds below 30 km/h, they can produce a noise almost 4 dB(A) lower than a combustion engine-powered vehicle (Verheijen and Jabben, 2010; Wogalter *et al.*, 2001). Thus, generalized adoption can significantly reduce the levels of environmental noise and related subjective annoyance. However, there is the risk of an increase in the number of accidents involving vulnerable road users – which already make up for a large part of the number of road deaths and injuries (European Commission, 2018b; Hu and Cicchino, 2018; Olszewski *et al.*, 2019) – due to misperception of approaching vehicles.

Understanding how low noise emission affects the vehicles' detection and localization by pedestrians (Barton *et al.*, 2013; Barton *et al.*, 2012), particularly by blind or visually impaired ones (Emerson *et al.*, 2013; Emerson *et al.*, 2011; Guth *et al.*, 2005; Wiener *et al.*, 2006), has been a challenge. When crossing a road, pedestrians must detect traffic, combine data coming from various directions, determine whether the time remaining before a vehicle reaches them is long enough for crossing, and adapt their action to the continuous perception of oncoming vehicles. The way they can determine the available time to cross and relate it to the time needed to cross is a behavioural indicator. Theoretically, the crossing is possible if the available time is higher than the crossing time, but pedestrians usually allow for a safety margin (Lobjois and Cavallo, 2007).

Oxley *et al.* (2005) stated that crossing decision-making is mainly based on the visual information received by pedestrians, firstly, concerning the distance between the vehicles and the crosswalk or a front car, agreeing with the conclusions obtained by Simpson *et al.* (2003) and Cavallo *et al.* (2019), and then about the vehicles speed, in order to estimate its time of arrival. Despite the importance of the visual information on pedestrians' crossing decision-making, the auditory cues are also relevant for the detection and location of approaching vehicles (Barton *et al.*, 2013; Barton *et al.*, 2012; Emerson *et al.*, 2013; Emerson *et al.*, 2011; Verheijen and Jabben, 2010; Wiener *et al.*, 2006). Thus, sometimes, the approach of quieter vehicles can be noticed later than needed to ensure a safe crossing, especially at lower speeds. The level of noise also influences the pedestrians' ability to estimate the trajectory of the approaching vehicle. The greater is the noise emitted, the easier it is to detect and estimate its arrival time.

In this study, the influence of vehicular noise on pedestrian crossing decision-making was explored, comparing the effects of noise emitted by an electric vehicle, a gasoline vehicle, and a control condition where vehicle sound was absent. Contrary to previous works, different approaching speeds, trajectories, and the corresponding sound effects on the pedestrians' risk behaviour were also explored. The possibility that electric vehicles lead to worse estimations of the vehicle's trajectory and to a riskier behaviour was here hypothesized.

Therefore, an experimental study using a CAVE-like virtual reality environment in which participants were safely placed "within" the audio-visual crossing scenario was conducted. Participants could both see and listen to the oncoming car and decide whether to cross or not. Simulated environments allow for more controllability of the experimental variables than video-based naturalistic approaches. They also enable researchers to put participants in potentially dangerous crossing situations without compromising their safety (Cavallo *et al.*, 2019; Charron *et al.*, 2012; Dommes and Cavallo, 2011; Schwebel *et al.*, 2012; Simpson *et al.*, 2003). In the experiment reported here, car trajectories and audio signals were developed based on recordings of speed and audio of real vehicles, and virtual scenarios were modelled based on actual streets to serve as context. This approach aimed to produce as realistic as possible visual and auditory cues to increase the ecological validity of the experiment.

With an exception for some changes executed due to the formatting and organization of global information in this document, this chapter integrally presents the work:

- Soares, Silva, Pereira, Silva, Sousa & Freitas. (2020). The Influence of Noise Emitted by Vehicles on Pedestrian Crossing Decision-Making: A Study in a Virtual Environment. Applied Sciences, 10(8), 2913. doi: http://dx.doi.org/10.3390/app10082913.

3.2. Materials and Methods

3.2.1 Participants

Ten adults aged 24–43 years old (m = 30.70; sd = 6.15; 50 % male) were recruited from the University of Minho community, in Portugal. Before the experiment, all participants answered a questionnaire regarding their hearing, visual, and mobility conditions. None of them reported any impairing condition. All participants gave their written informed consent. The experiments were conducted in accordance with the principles stated in the 1964 Declaration of Helsinki.

3.2.2 Virtual environment

Two existing real-world streets were modelled in two different virtual scenarios: 25A street, in Braga, and TP street, in Guimarães. Each one followed a similar development process. First, dimension and distance measurements were taken from the streets, including the length and width of the crosswalks and its markings, the road width, the width of the sidewalks, the length and width of the parking places, and the sizes of the road. Afterward, the two scenarios were modelled in Blender 2.79a (Blender Online Community, 2018), an open-source 3D computer graphics software that uses Python as a scripting language. Several architectural details such as buildings, vertical signalization, and vegetation were modelled, and textures from pavements and buildings were added to provide participants with a more realistic depiction of the roads (Figure 3.1(a)(b)).

(a) (b)

Figure 3.1 – The two virtual scenarios: (a) 25A; and (b) TP.

The next step was to model the movement of a vehicle, which approached the participants throughout the experiment. To do so, the traffic on the two streets was firstly analysed, recording vehicle speeds and trajectories when approaching the crosswalk in situations in which pedestrians were crossing the road. Then, noise recordings of real vehicles were carried out in a closed urban road to obtain a realistic depiction of the vehicles' noise resulting from similar trajectories.

To collect the speeds and trajectories of the vehicles, a 2-h video was recorded in each street and then analysed using the Traffic Intelligence software (Jackson *et al.*, 2013; Saunier *et al.*, 2010). The several trajectories collected were clustered into three distinct categories: (1) the vehicle maintained its speed without any or with very subtle changes (Constant Speed); (2) the vehicle slowed down before reaching the crosswalk but continued its trajectory without stopping (Slow Down); and (3) the vehicle slowed down and completely stopped before reaching the crosswalk (Stop). For each speed pattern, the mean (m), maximum (max), minimum (min), and standard deviation (sd) of the distances between vehicle and pedestrians at the beginning (V_i and D_i) and the end (V_f and D_f) of the braking, in the cases where it occurred, were calculated. These values (Table 3.1) were used as a reference to define the vehicles' trajectories to be used in the simulator. Contrary to other studies that usually assume constant speed (*e.g.* (Cavallo *et al.*, 2019; Dommes and Cavallo, 2011; Dommes *et al.*, 2012; Feldstein *et al.*, 2016; Meir *et al.*, 2015; Simpson *et al.*, 2003; Zito *et al.*, 2015)) the three types of speed profiles recorded in the observational study were implemented in the simulator.

Speeds above 30 km/h were not considered since the study intended to evaluate the pedestrians' crossing decision-making, considering the approach of a vehicle at short distances from the crosswalk. In addition, above that speed, the noise emitted by a vehicle is predominantly produced by the tire-road interaction, and engine noise differences (electric and gasoline combustion) are of little relevance to the crossing decision (Verheijen and Jabben, 2010).

Table 3.1 – Mean, maximum, minimum, and standard deviation of vehicle distance to the crosswalk for Stop and Slow Down movement patterns.

	Stop		**Slow Down**	
	D_i (m)	**D_f (m)**	**D_i (m)**	**D_f (m)**
m	15.8	5.71	16.72	7.01
sd	5.62	2.4	6.21	4.14
max	27.37	14.06	28.2	22.04
min	6.58	1.26	2.94	2.69

From the values of Table 3.1, three different conditions for the simulator experiment were defined (Table 3.2). The distance at which the vehicle was shown on the screen and started its approaching movement ($D_{i,\,mov}$) was kept the same in all conditions.

The vehicle approaching sounds were recorded using as test vehicles: (1) a Kia Ceed SW, with a gasoline combustion engine, equipped with ContiEcoContact3 195/65-R15 tires; and (2) a Renault Zoe ZE, with electric engine, equipped with Michelin Primacy 3 205/45-R17 tires. Controlled Pass-By (CPB) measurements were performed with a Brüel & Kjaer Pulse Analyzer type 3560-C and a Brüel & Kjaer Head and Torso Simulator (HATS) Type 4128-C equipped with Ear Simulators Type 4158-C and 4159-C. The HATS was placed at 1.55 m from the road centre, at the height of 1.66 m (corresponding to the

Portuguese population average height) with its head turned 35° counterclockwise from the road perpendicular.

Table 3.2 – Characteristics of vehicle movement in the different conditions presented in the experiment.

Conditions	**V_i (km/h)**	**V_f (km/h)**	**$D_{i,\,mov}$ (m)**	**D_i (m)**	**D_f (m)**	**Speed Pattern**
1	30	30	30	-	-	Constant
2	30	10	30	25	5	Slow Down
3	30	0	30	20	5.50	Stop

To minimize the environmental noise interference all recording sessions were performed with dry pavements, wind speed below 5 m/s, atmospheric temperature between 5 °C and 30 °C, and pavement temperature between 5 °C and 50 °C as recommended in ISO 11819-1 (1997) (Freitas *et al.*, 2012), between 20:00h and 24:00h. To generate the sound for each sample, the two vehicles completed the trajectories defined by the parameters in Table 3.2. To gather real speed, time, and distance data from the vehicles, their position was registered at each 0.125 s at the same time the sound recordings were performed. The sound and vehicles' positions files were later synchronized, calibrated, and implemented in the virtual environment.

3.2.3 Stimuli

Three different auditory conditions were used: (i) the vehicle emitted the noise of a car with a gasoline combustion engine; (ii) the vehicle emitted the noise of a car with an electric engine; and (iii) the vehicle emitted no sound. The third type of stimulus was considered as a control condition to assess the role auditory cues play in crossing decision-making.

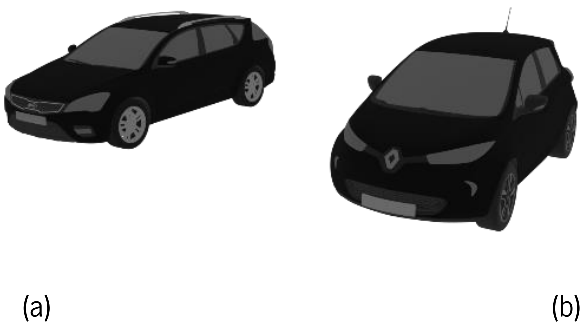
Table 3.3 presents the main characteristics of the stimuli audio component. The measurement time corresponds to the interval between the beginning of the stimulus presentation and the instant when the vehicle stopped or passed by the participant. As expected, the noise emitted by gasoline combustion vehicle was in general louder than that emitted by electric vehicle. The difference between the noise indicators for electric and gasoline combustion vehicles is bigger for the stimuli regarding the Slow Down pattern and lower for the Constant speed pattern. Each one of the three conditions presented in Table 3.2 and Table 3.3 was repeated five times for every auditory condition (electric engine (electric), gasoline combustion engine (gasoline), and no auditory cue (no sound)). Thus, in total, throughout the experiment, 90 stimuli were presented to each participant in a random order (3 speed patterns × 3 auditory conditions × 2 scenarios × 5 repetitions).

The virtual models of the approaching vehicle used in the experiment were a Kia Ceed SW (Seoul, South Korea, Kia Motors, 2011) for gasoline condition (Figure 3.2 (a)) and a Renault Zoe ZE (Boulogne, France, Renault S.A., 2018) for electric condition (Figure 3.2 (b)). For the no sound, the visual aspect of the vehicle varied between both models.

Table 3.3 – Acoustic characteristics of the stimuli regarding the electric and gasoline combustion vehicles.

Indicator[1]	Speed Pattern					
	Constant		Slow Down		Stop	
	Gasoline Engine	Electric Engine	Gasoline Engine	Electric Engine	Gasoline Engine	Electric Engine
LAmax (dB(A))	77.49	74.87	66.15	60.6	64.28	61.45
L5 (dB(A))	76.95	74.26	65.54	60.32	63.8	61.11
L10 (dB(A))	76.55	73.57	64.81	60.11	63.57	60.99
L50 (dB(A))	67.98	65.75	61.60	51.83	60.22	59.24
L90 (dB(A))	63.23	60.61	57.94	47.44	56.26	51.31
Measurement time (s)	3.90	4.05	7.20	8.55	5.40	5.10
Dynamic range (dB(A))	32.83	30.21	21.50	15.94	19.62	16.79

[1] values of the acoustic indicators for the sound acquired by the HATS's left channel (left ear).



(a) (b)

Figure 3.2 – Visual models of the vehicle used in the experiment: (a) Kia Ceed SW; (b) Renault Zoe ZE.

3.2.4 Instruments

The experiment was conducted in a room where the CAVE type system is located. Three DLP Christie Mirage S + 4K projectors with a resolution of 1400 × 1050 pixels are placed side by side generate an 8 m wide scene on a 9 m projection screen. They are capable of 3D stereoscopic projection, which was used with a frame rate of 60 fps. Participants, wearing 3D glasses were placed on the opposite side of the screen. The computational effort was distributed through 4 Dell Precision R7610 rack workstations, equipped with Nvidia Quadro K5000 graphics card and Intel Xeon E5 - 2600 processors. Three of them were used to render the projection itself, while the fourth was used for monitoring. BlenderVR software (Katz *et al.*, 2015) was used to control the simulation, paired with a VICON motion capture system. VICON reflective tracking points were placed on a set of headphones worn by participants. By knowing the position of the participants, it was possible to adjust the visual scene to their perspective, increasing the feeling of presence.

The room was kept dark throughout the experiments, with the exception of the projection and the VICON's infrared lights. Participants were placed at 2 m from the screen, rotated so that their sagittal plane formed a 35° angle with the screen. The projection viewpoint was such that the participant was placed on the sidewalk of the virtual scenario, facing the road. CPB sounds were played synchronously with the corresponding visual stimuli on the headphones, using VLC media player. The sound was amplified through a Sony TA-AV570 Audio Video Amplifier. Acoustic levels were calibrated to ensure they were equal to the ones registered during the recording sessions.

3.2.5 Experimental procedure

While listening to the instructions, participants were placed in the predefined location, where they remained throughout the experiment. They were equipped with the head tracker and the 3D glasses and asked to hold a computer mouse. They were tasked with indicating, in each trial, the moment when they decided to cross the street if they felt safe to do that, clicking on any button of the mouse. They were also instructed to avoid moving or rotating their heads as much as possible during the experiment to minimize the difference between the virtual and the perceived position of the sound source (vehicle). The experimental scene was set so that the participants could see the vehicle from the start of the stimulus presentation.

Participants completed an experimental session formed by two main blocks, one using the 25A scenario and others using the TP scenario. The experiment was preceded by a training block composed of 4 stimuli. Depending on the participants, there was a gap of 5 min between the two main blocks. The stimulus presentation continued after every click. However, participants were instructed to make their decision before the car stopped or passed by them, and the crossings were considered valid only for those cases.

3.2.6 Analysis

The influence of the several variables addressed in this study on the participants' crossing decision-making was analysed in terms of percentage of crossings, to infer about the impact of the considered variables (speed pattern and auditory condition) on the effective decision of the participants; response time, to evaluate the time that the participants needed to make their decision when they decided to cross; and TTP, which, although indirectly related to the response time, can ultimately serve as a risk-taking indicator. Here, lower TTPs at the crossing moment were assumed to be indicative of a riskier behaviour, as the participant would have less time to cross the road in a real situation.

The percentage of crossings was calculated, for each participant, considering the number of answers, *i.e.*, the trials for which they have clicked the computer mouse before the vehicle has stopped or passed in front of them, and the total number of trials per condition. For those trials in which the participant did not click, it was assumed that the participants would only cross after the vehicle passed, and no conflict was considered. The response time, which was the time from the start of the stimulus presentation to the moment the participant clicked the mouse, was also registered. The TTP was calculated based on Expression 2.2.

As mentioned in section 3.1., an impact of the noise level on the participants' decision-making was expected. With stimuli with higher noise levels, such as those related to the approach of the gasoline vehicle (see Table 3.3), the participants would be able to better estimate the vehicle's trajectory and would risk less, which would be translated into higher TTP values and a lower percentage of crossings. A faster decision-making for the gasoline vehicle due to the facilitated trajectory estimation was also expected. In turn and following the same increased saliency of the approaching cues, faster decisions and less risky behaviour for electric vehicles when compared with those in which no sound was presented were also expected to be found.

The influence of the variables such as the *auditory condition* and the *vehicle speed pattern* on the *percentage of crossings* was assessed using a three-way repeated-measures ANOVA and Bonferroni-corrected post-hoc tests. Due to the presence of missing values in the database regarding the trials that participants did not feel safe to cross, LMMs were used to assess the influence of the *auditory condition* and the *vehicle speed pattern* on *response time* and on *TTP*, accounting for repeated measures.

3.3. Results

3.3.1 Percentage of crossings

Figure 3.3 shows the percentage of crossings for all experimental conditions. In general, participants based their decision on the movement of the vehicle, in terms of speed and distance, crossing mainly during trials where the vehicle speed decreased.

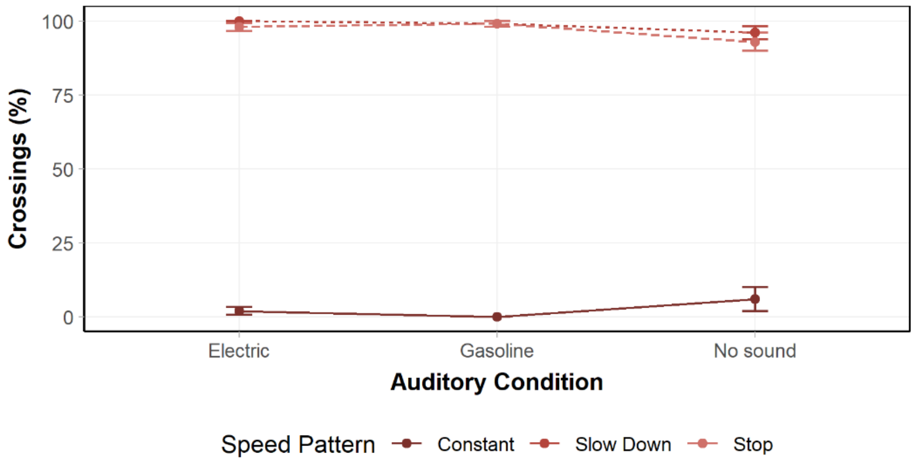


Figure 3.3 – Percentage of crossings and respective mean, standard error as a function of auditory condition, per vehicle speed pattern.

Although slight differences in the percentage of crossings could be observed, namely between no sound and the other two auditory conditions, it is not possible to state that the type of sound emitted by the vehicle, or its absence, has influenced the percentage of crossings. The very low percentage of crossings in the Constant speed stimuli should also be highlighted. The participants did not feel, overall, that it was safe to cross when a vehicle signals no intent of slowing down, and in the particular case of the gasoline condition, none of the participants decided to cross during in these conditions.

These observations are confirmed by a two-way repeated-measures ANOVA which analyse the role of *auditory condition* and the *vehicle speed pattern* as factors affecting the crossing decision. The auditory condition did not significantly influence the participants' percentage of crossings, $F(2, 18) = 0.90$, $p = 0.43$, while main effects were found for speed pattern, $F(2, 18) = 1580.54$, $\eta^2 = 0.99$, $p < 0.01$. Bonferroni post-hoc test indicated that the percentage of crossings did not significantly differ between the Stop (m = 96.67 %; sd = 6.61 %) and Slow Down (m = 98.33 %; sd = 4.61 %) patterns, but they were significantly higher than that regarding Constant speed pattern (m = 2.67 %; sd = 7.85 %).

A significant auditory condition × speed pattern interaction on participants' percentage of crossings was also found, $F(4, 36) = 2.89$, $\eta^2 = 0.24$, $p = 0.04$. However, considering the results shown in Figure 3.3, the effect of this interaction was mainly due to the great relevance of the speed pattern effect on the percentage of crossings and not exactly to that regarding the interaction between the two variables, as shown by the small effect size value (η^2). Bonferroni post-hoc test indicated the percentage of crossings is only significantly different when the auditory conditions at Constant speed (electric: m = 2.00 %; sd = 4.22 %; gasoline: m = 0 %; sd = 0 %; no sound: m = 6.00 %; sd = 12.65 %), Slow Down (electric: m = 100.00%; sd = 0 %; gasoline: m = 99.00 %; sd = 3.16%; no sound: m = 96.00 %; sd = 6.99 %), and Stop (electric: m = 98.00 %; sd = 4.22 %; gasoline: m = 99.00 %; sd = 3.16 %; no sound: m = 93.00 %; sd = 9.49 %) patterns were compared. No significant differences existed between the percentage of crossings referring to the different auditory conditions verified for the Stop and the Slow Down patterns.

3.3.2 Response time

Figure 3.4 shows the aggregated cumulative percentage of crossings as a function of time. It is noticeable that the few crossings with Constant speed stimuli all occurred in the initial 2 s after the beginning of the stimuli presentation. For the other speed patterns, there were considerably more crossings. Nevertheless, in both the Slow Down and Stop conditions, most responses were given after the vehicle speed began decreasing.

The response time was examined with a LMM considering the *vehicle speed pattern* and the *auditory condition* variables. The time participants have taken to respond was significantly longer when the vehicle stopped (m = 3.88 s; sd = 0.86 s; $p < 0.01$) and when it just slowed down (m = 3.15 s; sd = 0.87 s; $p < 0.01$) than when it passed at constant speed (m = 1.36 s; sd = 0.41 s). The response time was significantly longer for the approaching eletric vehicle (m = 3.52 s; sd = 0.99 s) than for the gasoline combustion one (m = 3.40 s; sd = 0.79 s; p = 0.05). The no sound condition (m = 3.53 s; sd = 1.10 s; p = 0.44) did not significantly differ from the electric one.

It is important to mention that existing differences between response times obtained for the gasoline vehicle and the other conditions may be partially explained by a small difference in the speeds used by the model defining movement of the cars, recorded along the passage of the vehicle when the noise was acquired. During the acquisitions, the two cars were driven by the same person to minimize the human error induced in the speed control. However, due to the different sensitivity of the vehicles' systems and human factors of the professional driver, some differences in the order of 1.70 km/h, on average, were found in the vehicle speed.

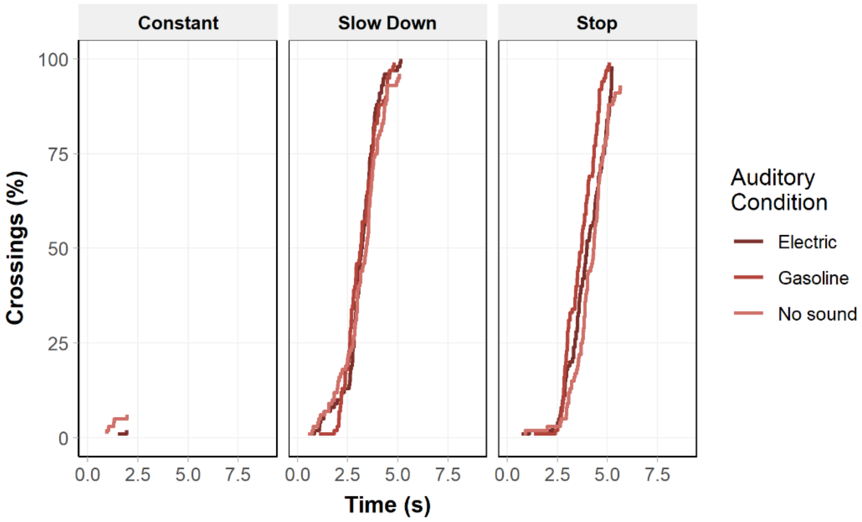


Figure 3.4 – Percentage of cumulative crossings aggregated for all participants as a function of response time.

Figure 3.5 shows the number of crossings and corresponding response time per participant in each condition. Only 2 out of 10 participants felt able to cross the road when the vehicle was approaching them at 30 km/h. Besides also being the only ones to cross during the Constant speed condition, these two were also the ones who made crossing decisions more quickly in the other conditions. The results are remarkably consistent, and Figure 3.5 exhibits the low variability in the responses of all participants.

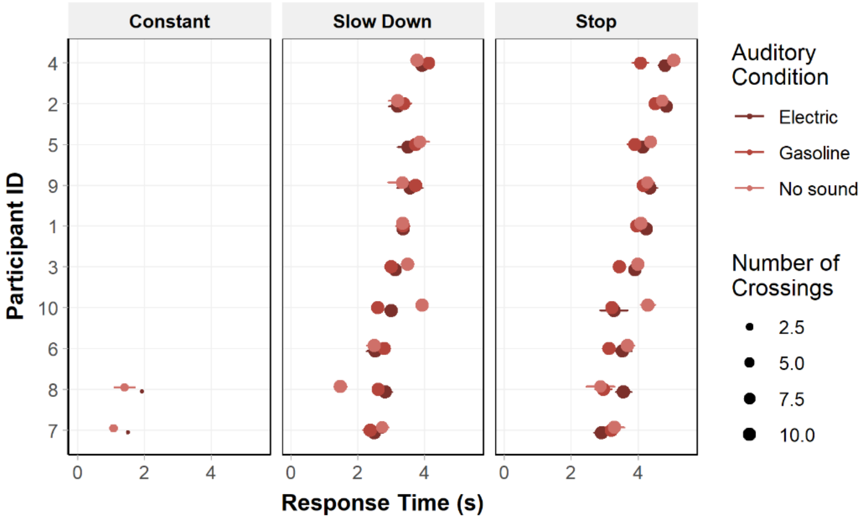


Figure 3.5 – Distribution of the number of crossings with the mean standard error (horizontal lines) of the response time, by the participants, as a function of response time, per speed pattern and auditory condition.

Considering all the results of the analysis of the percentage of crossings and the response time, it is noticeable that the participants felt more opportunities to cross the road safely when the vehicle speed varied, namely in stimuli where the car had the pattern of stopping and slowing down. In the responses given by the participants to the stimuli related to the Stop speed pattern, it was possible to verify some differences between the different auditory conditions. In these cases, and for the gasoline combustion vehicle, participants made their decision more quickly than in the other two types of stimuli.

3.3.3 Time-to-passage

The values of TTP were very similar across conditions. Nevertheless, a slightly lower value of TTP for the Stop and Constant speed conditions was noticeable when compared with the Slow Down condition. Regarding the type of auditory condition, lower values of TTP were found when the gasoline vehicle approached than in the others. The highest values of TTP were found in no sound condition (Figure 3.6).

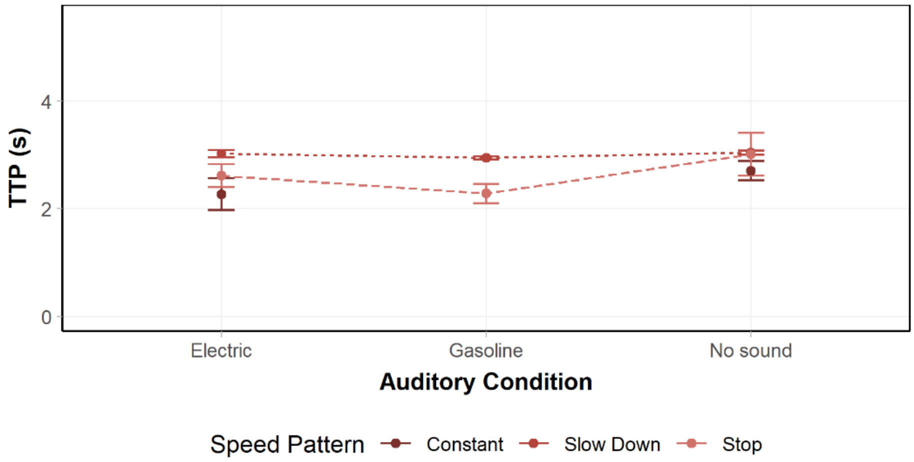


Figure 3.6 – Mean TTP and respective mean standard error as a function of auditory condition, per vehicle speed pattern.

The results of the LMM confirmed what is shown in Figure 3.6. The auditory condition had a significant influence on the TTP. The obtained values of TTP regarding the no sound stimuli (m = 3.01 s; sd = 1.34 s; p = 0.02) were significantly higher than those obtained with the approaching of the electric vehicle (m = 2.80 s; sd = 0.83 s). When the gasoline combustion vehicle (m = 2.61 s; sd = 0.81 s; p = 0.04) approached the participants, the TTP was significantly lower than observed for the remaining auditory conditions. Regarding the speed pattern, the results of the model showed the TTP for the Slow Down (m = 3.00 s; sd = 0.30 s; p = 0.40) and Stop (m = 2.62 s; sd = 1.42 s; p = 0.81) patterns was not significantly different from that verified for the Constant speed pattern (m = 2.59 s; sd = 0.44 s).

Because TTP is the result of dividing the vehicle distance by the approaching velocity, the role of these two components was analysed in more detail. Two LMMs were developed to assess the influence of the auditory condition on the distance at which the vehicle was and the speed it was going at the moment the participants decided to cross. The analysis in Figure 3.7 shows that these distances were very similar in all auditory conditions, considering each speed pattern separately.

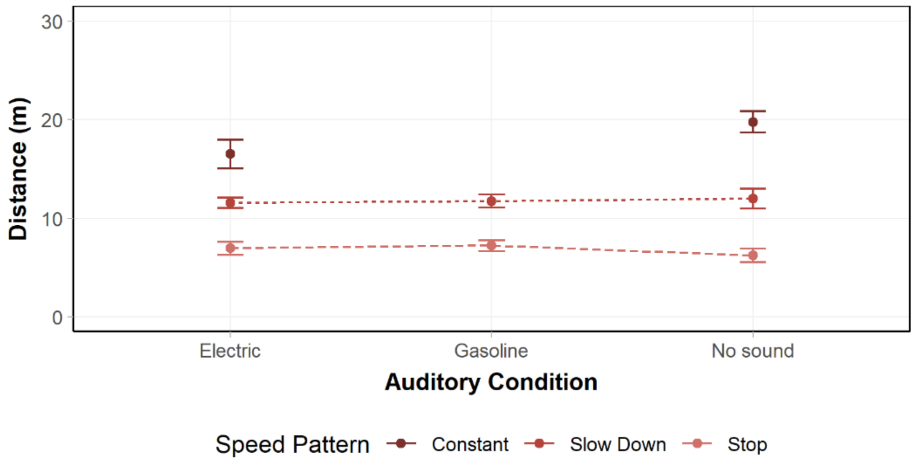


Figure 3.7 – Mean distance between the vehicles and participants at the moment of the participants' responses and respective mean standard error as a function of auditory condition, per vehicle speed pattern.

The results of the model show that the recorded distances at the moment of response did not differ in the no sound condition (m = 9.45 m; sd = 4.98 m; p = 0.70) or in the gasoline condition (m = 9.50 m; sd = 3.54 m; p = 0.39) when compared with those registered when approaching the electric vehicle (m = 9.37 m; sd = 4.12 m). Nevertheless, this variable appeared to be affected by the vehicle speed pattern. In the Stop pattern (m = 6.82 m; sd = 3.03 m; p < 0.01) the registered distances were shorter than those of the Slow Down pattern (m = 11.76 m; sd = 3.53 m; p < 0.01), which, in turn, were shorter than the Constant pattern (m = 18.94 m; sd = 2.78 m).

Regarding the vehicle speed at the moment of the participants' response, Figure 3.8 shows a great similarity between the three auditory conditions. However, in the results of the Stop pattern stimuli, the participants crossed with higher vehicle approaching speeds when they were presented with the sound of a gasoline combustion vehicle. The model results show that in fact the vehicle speed at the moment of response was significantly higher for gasoline stimuli (m = 13.72 km/h; sd = 4.92 km/h; p = 0.02) than for electric stimuli (m = 12.85 km/h; sd = 5.51 km/h). Non-significant differences were found between the speeds of the no sound (m = 12.47 km/h; sd = 6.34 km/h; p = 0.13) and electric condition.

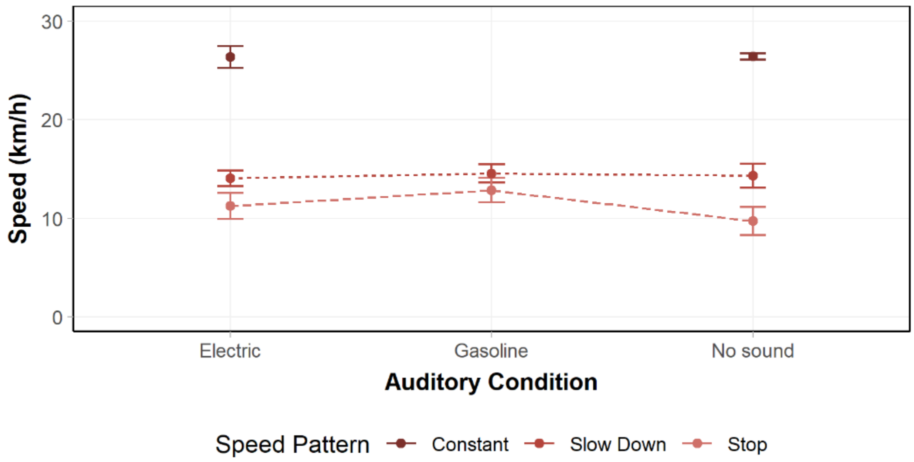


Figure 3.8 – Mean speed of the vehicle at the moment of the participants' response and respective mean standard error as a function of auditory condition per vehicle speed pattern.

As in the case of distance, the vehicle approaching speed at the time of the participants' cross significantly depended on the vehicle speed pattern. In the Stop pattern (m = 11.34 km/h; sd = 5.96 km/h; $p < 0.01$), the registered speeds were lower than those of the Slow Down pattern (m = 14.31 km/h; sd = 4.43 km/h; $p < 0.01$), which, in turn, were lower than those of the Constant pattern (m = 26.37 km/h; sd = 0.93 km/h). Nevertheless, one should regard the differences between the Constant pattern and the other conditions with care, due to the lower number of observations (*i.e.*, lower number of crossing decisions) in this particular condition.

3.4. Discussion

On the one hand, pedestrian crossing decision-making appears to be based mainly on the readily assessable visual information of an approaching vehicle, specifically its speed and distance (Oxley *et al.*, 2005), on the other hand, auditory cues can play an important role in both detecting and improving locating of approaching vehicles (Barton *et al.*, 2013; Barton *et al.*, 2012).

The increasing presence of hybrid and electric vehicles raises important questions about the impact of auditory cues on pedestrian safety, especially in situations of conflict between pedestrians and vehicles, such as in cases of crossing the road when a vehicle is approaching (Emerson *et al.*, 2013; Emerson *et* *al.*, 2011; Wiener *et al.*, 2006; Wogalter *et al.*, 2001). The purpose of this study was to contribute to this ongoing discussion by assessing the influence of the type of sound emitted by a vehicle and the auditory cues on pedestrian crossing decision-making, without neglecting the role of the vehicle speed and distance, as well as its movement pattern.

Three types of stimuli were presented to the participants, corresponding to the approach of a vehicle with different movement characteristics: a vehicle emitting the sound of an electric car, a vehicle emitting the sound of a gasoline combustion car, and a vehicle with no audio component.

The results show that, contrary to the hypothesis of this study, the type of emitted sound had a negligible influence on the number of times the participants decided to cross the road. On the other hand, the movement pattern of the approaching vehicle seemed to play a more relevant role.

In general, participants only chose to cross when the vehicle displayed signs of slowing down. For a vehicle initial distance of 30 m and a constant speed of 30 km/h, most participants assumed that it was not safe to cross the road. The analysis of the number of crossings as a function of response times confirmed this conclusion. At Constant speed stimuli, the very few crossings occurred at an early stage of the stimulus presentation, while, in stimuli where the vehicle speed decreased, the participants waited for the approaching vehicle to reach lower speeds in order to communicate their decision to cross.

The gasoline combustion vehicle seemed to lead to faster crossing decisions, particularly in the Stop condition. However, this also meant that participants crossed when the speed was still relatively high, which, counter-intuitively, resulted in lower TTP values at the time of crossing decision. The shorter response times for gasoline could, at first view, indicate a better trajectory estimation for louder vehicles. However, a difference was not found between the electric and no sound conditions. In addition, when analysing vehicle distances and speeds at the time which the responses were given, it is apparent that the participants' decision was based primarily on the vehicle distance, which was specific for each vehicle speed pattern. For each of the three different auditory conditions, participants clicked on the computer mouse when the vehicle was always at the same distance. That distance selected by the participants was greater for higher approaching speed conditions. Expectably, the similarity in distances should have been accompanied by similarities in vehicle speed, if the vehicle speed and its evolution over time were exactly the same in the three types of auditory condition. In such cases, no difference would have been observed in the TTP values and response times when the three auditory conditions were compared. However, differences in speed of about 1.7 km/h existed between conditions, resulting from the manual driving variability during the CPB and movement trajectories acquisition sessions. This difference contributes to explain the slightly lower TTP values for gasoline vehicle in the Stop condition.

Another possible influencing factor is that visual model of the car presented during these two auditory conditions was different (Kia Ceed for gasoline combustion vehicle trials and Renault Zoe ZE for the electric vehicle trials), and the physical characteristics (such as dimension) of the vehicle can be important for the visual looming perception (Yannis *et al.*, 2013).

The results of this work support the view that pedestrians make crossing decisions based mainly on the movement characteristics of the approaching vehicle, using visual information to estimate the safeness of crossing the road (Cavallo *et al.*, 2019; Oxley *et al.*, 2005; Simpson *et al.*, 2003). However, they also indicate that the speed of the approaching vehicle may have an important role in the decision process, supporting the most common view that the distance of the oncoming vehicle is the most important parameter in crossing decision-making (Cavallo *et al.*, 2019; Simpson *et al.*, 2003). Considering the testing conditions implemented in this work, it is possible to state that for situations in which only one vehicle approaches the crosswalk from a short distance and with no occlusion to the pedestrian's visibility, the sound does not seem to be the most meaningful cue for the pedestrians' crossing decision-making.

Overall, the conclusions of Verheijen and Jabben (2010), who pointed electric vehicles as more dangerous for pedestrians, at least for situations in which detection has already occurred, could not be verified. The number of times that participants crossed when faced with an approaching electric vehicle was very similar to the number of times that participants crossed when faced with a gasoline vehicle. Moreover, the approaching speed at the moment of crossing decision was lower for trials with electric vehicles, thus allowing participants to cross more safely.

It is worth noting the distinction between the trajectory and speed estimation, which is the object of this study, and vehicle detection. Even considering that the trajectory of the electric car can be estimated with the same precision as the gasoline combustion one, the first can still be more dangerous because it can be much more difficult to detect in situations that pedestrians are not looking at it or have an obstacle occluding the approaching vehicle due to the lower levels of noise emitted by this type of vehicles.

Finally, the differences in crossing percentages as a function of speed pattern are regard to be as a quite relevant conclusion. Contrary to other studies that usually assume constant speed (*e.g.* (Cavallo *et al.*, 2019; Dommes and Cavallo, 2011; Dommes *et al.*, 2012; Feldstein *et al.*, 2016; Meir *et al.*, 2015; Simpson *et al.*, 2003; Zito *et al.*, 2015)), this study showed that the speed pattern is a relevant factor of crossing decision-making and should be a variable of interest in pedestrian simulator studies. Future work should complement this approach with other vehicle approaching patterns. Implementing different speeds and variations of the initial distance, as well as simulating different visibility conditions to the approaching vehicle, would be an interesting improvement aiming to clarify a possible impact of the sound emitted by the vehicle on the participants' crossing decision-making.

3.5. Conclusions

The aim of this part of the study was to analyse the importance of auditory cues and, more specifically, how the type of noise emitted by vehicles can affect pedestrian crossing decision-making. In a virtual scenario, three types of stimuli corresponding to the approach of a vehicle were presented to the participants: a vehicle emitting the sound of an electric car, a vehicle emitting the sound of a gasoline combustion engine car, and a vehicle that did not produce any sound. Three types of speed patterns were considered based on observational data: Constant speed, Slow Down, and Stop patterns. The sound emitted by the simulated vehicles consisted of samples collected through controlled pass-by measurements in a semi-controlled environment.

The results show that the movement characteristics of the approaching vehicle, the speed, and especially the distance, were determining factors on the participants' crossing decision. On the other hand, the sound emitted by the approaching vehicle, or its absence, does not seem to be a meaningful factor as expected for explaining participants' crossing decision-making, at least in scenarios where participants are crossing a road having perfect visibility conditions of the approaching vehicle.

Moreover, this enhanced simulator proved to be a useful tool in the study of pedestrian crossing decision-making.

4. THE IMPACT OF THE AUDITORY CUES AND VEHICLE'S KINEMATICS ON PEDESTRIANS' CROSSING DECISION-MAKING

4.1. Introduction

Over the past 20 years, the number of road traffic fatalities in Europe has been diminishing continuously due to new road safety policies and regulations. However, data from the Community database on Accidents on the Roads in Europe (CARE) shows that, since 2013, the reduction trend has been slowing down. This appears to be driven by an increase in the number of car crashes involving young people and a slower than expected decrease in fatalities involving Vulnerable Road Users (VRUs) (European Commission, 2018a; Gicquel *et al.*, 2017). Pedestrians, in particular, make up a large part of the number of road deaths and injuries (European Commission, 2018b; Hu and Cicchino, 2018; Olszewski *et al.*, 2019).

Unsurprisingly, most crashes involving pedestrians occur when they attempt to cross the road in the face of incoming traffic (Lassarre *et al.*, 2007). Significant risk factors are well identified, namely, (1) environmental factors, *i.e.* those regarding all the physical environment surrounding the pedestrian when crossing the road at a given crosswalk, such as road design, traffic density, average traffic speed and visibility (Ewing and Dumbaugh, 2009; Ezzati Amini *et al.*, 2019; Granié *et al.*, 2014; Stoker *et al.*, 2015; Sucha *et al.*, 2017; Turner *et al.*, 2006; Zegeer *et al.*, 2006), (2) socio-demographic characteristics of the pedestrians crossing the road and of the place where the study section is inserted, such as pedestrians' age and gender, and population density, respectively (Bernhoft and Carstensen, 2008; Hamed, 2001; Holland and Hill, 2007; Johansson *et al.*, 2004; LaScala *et al.*, 2000; Liu and Tung, 2014; Moyano Díaz, 2002; Papadimitriou *et al.*, 2016a; Rosenbloom *et al.*, 2008), and (3) situational factors relative to each crossing situation, such as speed and distance of the approaching vehicle during the crossing (Granié *et al.*, 2014; Hine, 1996; Liu and Tung, 2014; Oxley *et al.*, 2005; Papadimitriou *et al.*, 2016a; Papadimitriou *et al.*, 2009; Simpson *et al.*, 2003; Sucha *et al.*, 2017; Várhelyi, 1998; Yannis *et al.*, 2013).

Regarding situational factors, a relevant part of the existing literature on pedestrian safety is devoted to identifying which variables influence the decision-making process of pedestrians crossing the roadway

(Liu and Tung, 2014; Lobjois and Cavallo, 2007; Oxley *et al.*, 2005) and the human behavioural factors that affect it (Hine, 1996; Papadimitriou *et al.*, 2016a; Papadimitriou *et al.*, 2009). An ongoing discussion revolves around the question of whether pedestrians base their decision exclusively on an estimation of the available time to cross before the vehicle reaches the crosswalk or if they primarily consider the distance between them and the vehicle. In a seminal empirical work, Oxley *et al.* (2005) tested subjects of different ages in a crossing task in a virtual traffic environment. They observed that distance was a better predictor for crossing behaviour than time-to-arrival (TTA). Since then, numerous research works have been approaching the issue through both empirical and observational methods. An important observation is that this tendency to rely primarily on distance seems to be greater on the elderly (Liu and Tung, 2014; Lobjois and Cavallo, 2007; Oxley *et al.*, 2005) and young people (Connelly *et al.*, 1998). A possible explanation for this is that people in these two age groups may have a reduced ability to perceive and integrate the distance and speed of the approaching vehicle to estimate the available time to cross the road before it reaches their position.

A study by Feldstein and Peli (2020) seems to show that even young adults may rely on distance under less optimal conditions. They compared the crossing behaviour of young subjects in virtual (Head Mounted display - HMD) and real-world setups. They observed that participants based their decision primarily on distance in the virtual crossing task, while on the real-world they used time as main cue. They hypothesized that the low resolution of HMD may have prevented participants from properly assessing the speed of the vehicle, making them fall-back to a distance-based criterion. Taken together, these findings suggest that pedestrians may fall back from a time-based to a distance-based strategy when they have difficulties in estimating the vehicle's speed.

An important research gap in studies of pedestrian crossing behaviour and decision-making is the impact of the speed profile of the approaching vehicles. Most of the empirical studies conducted so far only consider vehicles with constant speeds (*e.g.* (Cavallo *et al.*, 2019; Dommes and Cavallo, 2011; Dommes *et al.*, 2012; Feldstein *et al.*, 2016; Feldstein and Peli, 2020; Lobjois and Cavallo, 2007; Meir *et al.*, 2015; Simpson *et al.*, 2003; Zito *et al.*, 2015)). Nevertheless, it is known that crossing decisions often occur in the course of a driver-pedestrian interaction, with the pedestrians deciding to cross when they believe the driver will yield the passage (Ackermann *et al.*, 2018; Mahadevan *et al.*, 2018; Schmidt and Färber, 2009). Misunderstandings are, however, common and often lead to crashes (Habibovic and Davidsson, 2012). Generally, it seems that pedestrians interpret speed reduction as an indication that the driver will yield (Dey *et al.*, 2019; Schneemann and Gohl, 2016; Soares *et al.*, 2020; Sucha *et al.*, 2017). However, exactly how the vehicle speed before deceleration and particular kinematics affect crossing behaviour is still not fully understood.

Another factor often disregarded in the analysis of crossing decisions refers to the role of the auditory cues produced by the moving vehicle. Some attention has been given to the auditory stimuli, mostly considering blind pedestrians, which must solely rely on their audio perception to make crossing decisions (Ashmead Daniel *et al.*, 2005; Emerson *et al.*, 2011; Guth *et al.*, 2005). Barton *et al.* (2012) analysed the detection and localization of approaching vehicles through auditory cues in sighted pedestrians. They concluded that higher speeds allow pedestrians to detect the vehicle approaching over greater distances, but lower speeds facilitate the judgment of when the vehicle is getting near them. Pugliese *et al.* (2020) analysed TTA judgments based on visual, auditory, and combined cues. Their results point to a higher relevance of the visual cues.

Here, an extension of the previous research presented in Chapter 3 (Soares *et al.*, 2020) is reported through a study that aims to clarify the role of the vehicle kinematics on pedestrians' crossing decision-making, mediated by the resulting visual and auditory cues. A more thorough analysis of the role of speed and distance, as well as the different speed profiles of the approaching vehicle, is also presented.

To do so, a virtual crossing simulator implemented through a CAVE-like, power wall setup was used. Participants were asked to visualize and hear an approaching vehicle in different conditions and decide if and when to cross by clicking on a computer mouse button. The use of simulators is becoming increasingly common for controlled pedestrian safety studies (Cavallo *et al.*, 2019; Charron *et al.*, 2012; de Clercq *et al.*, 2019; Deb *et al.*, 2017; Deb *et al.*, 2018b; Feldstein *et al.*, 2016; Meir *et al.*, 2015; Simpson *et al.*, 2003; Zito *et al.*, 2015). In the experiment reported here, a congruent auditory input recorded from real vehicles is provided with the visual input. This was intended to increase the feeling of presence experienced by the participants and to address one of the topics of this study, namely the auditory perception of approaching vehicles.

With an exception for some changes implemented due to the formatting and organization of global information in this document, avoiding the repetition of some previously presented information, this chapter consists of the work described on:

- Soares, Silva, Pereira, Silva, Sousa, & Freitas (2021). To cross or not to cross: Impact of visual and auditory cues on pedestrians' crossing decision-making. Transportation Research Part F: Traffic Psychology and Behaviour, 82, 202-220.
  doi: http://dx.doi.org/10.1016/j.trf.2021.08.014.

4.2. Materials and Methods

4.2.1 Participants

A sample of 30 adults (16 female and 14 male) with ages between 20 and 60 years old (m = 39.70 years old; sd = 12.11 years old) was recruited from the University of Minho community, Portugal. This age group corresponds to the segment of active population who is more likely to be found walking and crossing the road because of the daily commuting.

Prior to the experiment, all participants answered a questionnaire regarding their hearing, visual and mobility conditions. None of them reported any impairing condition that could interfere with participation in the experiment, such as some type of blindness, deafness, and problems impeding his/her movement. They also signed an informed consent form before participating in the experiments.

4.2.2 Virtual environment

The two same streets considered in Chapter 3 were chosen for this study: the 25 de Abril Street, in the city of Braga; and the Teixeira de Pascoais Street, in the city of Guimarães, both located in Portugal. The main characteristics of each street are presented in Table 2.2 and Table 2.3. They were chosen because they have the same number of lanes, crosswalks with similar lengths, and no major differences in the environment involving the crosswalk (*e.g.* the sidewalks' dimensions and the existence of similar buildings). Two streets were used (instead of just one) to minimize the risk of biases created by uncontrolled visual elements.

In order to avoid repeating the description of the scenario modelling process, information about that task can be read in section 3.2.2 of Chapter 3. Figure 4.1 and Figure 4.2 presents a comparison between the virtual scenario and the real depiction of each street.

(a) (b)

Figure 4.1 – Comparison between the (a) virtual and (b) real scenarios regarding the 25A Street.

(a) (b)

Figure 4.2 – Comparison between the (a) virtual and (b) real scenarios regarding the TP Street.

4.2.3 Stimuli

The development of the audio-visual stimuli relied on real-world information collected in a two-stage procedure. In the first stage, an observational study was conducted for characterizing the typical speed patterns for vehicles approaching crosswalks. In the second stage, a test vehicle was used to replicate the identified patterns in a controlled setting while the vehicle kinematic data and resulting sounds were recorded. Next, each of these stages is described.

4.2.3.1 Observational study

Firstly, the video recordings of pedestrian crossings involving approaching vehicles mentioned in section 3.2.2 of Chapter 3 were carried out in each of the selected streets. Videos were recorded at 30 fps, using a GOPRO 5 Black camera, with a resolution of 1920 × 1080 pixels. The camera was placed at the height of 5 m or more and between 15 and 25 m away from the crosswalk, depending on the conditions of each location. Each video had a duration of approximately 2 hours.

A more detailed video analysis than the one carried out in the study presented in Chapter 3 was performed using the Traffic Intelligence software (Jackson et al., 2013; Saunier et al., 2010). In short, for each recorded video, Traffic Intelligence identified and mapped the movement of each pixel, frame by frame, grouping them according to the similarity of their characteristics and classified each group as an object (pedestrian or vehicle). The software provided the trajectories and speed of both vehicles and pedestrians. A total of 126 observations were registered (68 on TP street and 58 on 25A street).

From the video analysis, the three most observed vehicle speed patterns in pedestrian crossing situations were identified and characterized: i) the vehicle slows down and completely stops before reaching the crosswalk (Stop); ii) the vehicle slows down before reaching the crosswalk but continues its trajectory without stopping (Slow Down); ii) the vehicle maintains its trajectory without any, or with very subtle, speed changes (Constant Speed). Descriptive statistics are presented in Table 4.1.

For the Stop and Slow Down patterns, V_i and D_i represent respectively the speed and distance between vehicle and pedestrians at the beginning of the observation and V_f and D_f represent speed and distance at the end of the braking phase of the trajectory. For the Constant speed pattern, V represents the average speed. For each variable, mean (m), maximum (max), minimum (min), and standard deviation (sd) values are presented.

Table 4.1 – Mean, maximum, minimum, and standard deviation of vehicle speed and distance to pedestrian for each speed pattern.

	Stop				**Slow Down**				**Constant Speed**
	V_i (km/h)	**D_i (m)**	**V_f (km/h)**	**D_f (m)**	**V_i (km/h)**	**D_i (m)**	**V_f (km/h)**	**D_f (m)**	**V (km/h)**
m	17.30	15.80	0	5.71	21.34	16.72	7.24	7.01	25.91
sd	8.15	5.62	0	2.40	8.46	6.21	6.56	4.14	7.87
max	34.41	27.37	0	14.06	37.59	28.20	28.39	22.04	43.18
min	3.81	6.58	0	1.26	4.43	2.94	1.07	2.69	14.27

The characteristics of the vehicle movement for the simulation (Table 4.2) were defined, taking into account the descriptive statistics presented in Table 4.1. The goal was to have a limited set of experimental conditions while still having representative values of V_i, D_i, V_f, and D_f.

Table 4.2 – Characteristics of vehicle movement in the different conditions presented on the experiment.

Condition	**V_i (km/h)**	**V_f (km/h)**	**$D_{i.\,mov}$ (m)**	**D_i (m)**	**D_f (m)**
1	20	20	35	-	-
2	30	30	35	-	-
3	20	20	30	-	-
4	30	30	30	-	-
5	20	20	25	-	-
6	30	30	25	-	-
7	30	10	30	25	5
8	20	10	30	15	10
9	20	0	30	15	5.50
10	30	0	30	20	5.50

Perhaps because pedestrians found it unsafe to cross, almost no crossings were observed for the selected distances and speeds above 30 km/h during the observational study. So, the conditions of the study were limited to speeds equal to or lower than this value. To decrease the likelihood of participants memorizing the vehicle's motion profiles and taking into account that in the Slow Down and Stop patterns the speed varied along the time of approaching, hampering some learning effect that could occur, the initial distance at which the vehicle appeared ($D_{i,\ mov}$) in the Constant speed stimuli also varied.

4.2.3.2 Auditory stimuli and trajectory acquisition

Following the approach used in the study described on Chapter 3, controlled binaural sound recordings of real vehicles were carried out in a closed urban road. The vehicles' noise was recorded using a Brüel & Kjaer Pulse Analyzer type 3560-C and a Brüel & Kjaer Head and Torso Simulator (HATS) Type 4128-C equipped with Ear Simulators Type 4158-C and 4159-C. The Controlled Pass-By (CPB) movement of a Kia Ceed SW with a gasoline combustion engine and equipped with ContiEcoContact3 195/65-R15 tires was used for the recordings.

CPB measurements include all vehicle noise sources, the effect of propagation mechanisms, and noise from the surrounding environment (Freitas *et al.*, 2012). For this reason, the recordings were performed during the night-time (20:00h – 24:00h) in a quiet zone to avoid traffic noise. To minimize the meteorological bias, all recording sessions were performed with dry pavement, wind speed below 5 m/s, atmospheric temperature between 5°C and 30°C, and pavement temperature between 5°C and 50°C as recommended in ISO 11819-1 (1997). Moreover, to represent the average conditions of the Portuguese urban roads, the sound recordings were performed in an asphalt mix (AC14) pavement with good maintenance conditions.

During the recordings, the HATS was placed with its head turned 35° from the road direction, on the side of the road, at 1.55 m from its centre, and 1.66 m height (Portuguese population average height). To generate the sound samples for each of the three types of vehicle motion pattern, a driver performed the trajectories defined by the parameters in Table 4.2. The real speed, time, and distance data from the vehicle were registered at 1/8 Hz rate simultaneously with the sound recordings.

The sound and vehicle position data were later synchronized, calibrated, and implemented in a virtual environment. The visual model of the vehicle used in the experiment was the same used in sound recordings.

4.2.4 Instruments

The experiment was conducted in the same room and using the same CAVE type system used in the study described in the previous chapter. For more information about the experimental setup and instruments used in this study, see section 3.2.4 of Chapter 3.

4.2.5 Experimental procedure

Before the beginning of the experiment, each participant was placed in a predefined room point (2 m from the projection screen) where they had to stay throughout the experiment (Figure 4.3). This point corresponded, in the virtual space, to the intersection of the perpendicular to the direction of the vehicle movement and crosswalk's axis of symmetry and the curb.

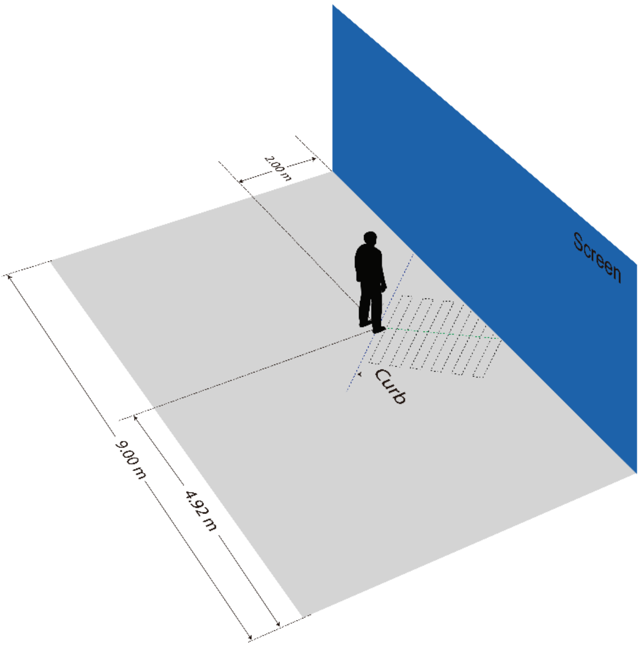


Figure 4.3 – Spatial layout of the room and participant position.

Participants were asked to put on the headset and the 3D glasses while listening to the instructions. They were then tasked with indicating, in each trial, the moment they decide to cross the street, clicking on the buttons of the mouse. They were also told not to press any button if they decided not to cross. Figure 4.4 shows a depiction of the experiment's performance.

Figure 4.4 – Participants' view during the performance of the experiment.

Participants completed an experimental session composed of two main blocks, one in each street scenario. The experiment was preceded by a training block composed by four crossing trials. Each one of the ten speed patterns presented in Table 4.2 was randomly repeated five times for each type of auditory condition (gasoline combustion engine – *audio-visual condition* and those without auditory cue – *no sound condition*). Participants went through 200 trials (10 movement conditions × 5 repetitions × 2 auditory conditions × 2 streets). The two main blocks were also split into two parts so that participants could rest between each part and block for as long as they needed. The experiment lasted 1 hour.

4.2.6 Analysis

As in Chapter 3, the influence of the variables addressed in this study on the participants' crossing decision-making was also analysed in terms of the percentage of crossings, response time, and TTP (see all the definitions in section 3.2.6 of Chapter 3). The influence of the variables *auditory condition*, *vehicle speed pattern*, *vehicle initial speed*, and *vehicle initial distance* on the percentage of crossings was assessed using a three-way repeated-measures ANOVAs. The influence on *response time* and *TTP* was assessed by fitting mixed-effects regression models with random effects included for the participant and fixed effects defined for the three variables mentioned above. The use of Linear Mixed Models is justified by the existence of missing values in the data, corresponding to trials in which participants did not cross. The data analysis was done in two distinct stages. In the first stage, the conditions characterized by constant speed patterns were analysed. In the second stage, a comparison was made between the different speed patterns.

4.3. Results

4.3.1 Constant speed pattern

Figure 4.5 shows the crossings' data for each participant and condition (location of the circle along the axis represents the mean response time, the size of the circle represents the number of crossings, and the line shows the standard error of the mean; participants are vertically ordered according to mean Response Time).

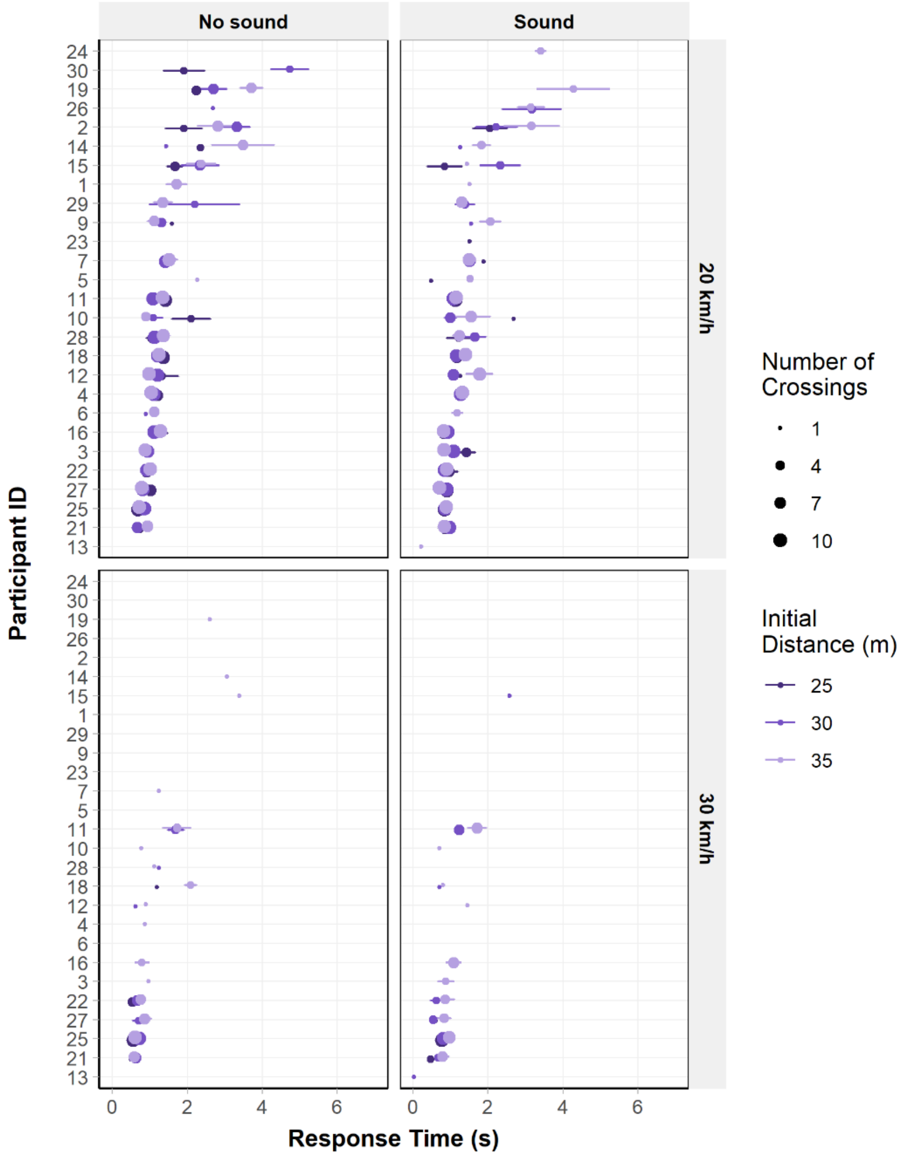


Figure 4.5 – Participants' responses along time of stimulus' presentation, per auditory condition and initial speed (Constant speed pattern).

It is possible to note a group of participants that frequently decided to cross, irrespective of the condition. These participants also made consistently faster decisions. The summary of descriptive statistics in terms of percentage of crossings, response time and TTP, regarding the analysis of the Constant speed pattern is presented in Table 4.3.

Table 4.3 – Descriptive statistics of the percentage of crossings, response time, and TTP for each trial and vehicle Constant speed pattern only.

			Crossings			**Response time**			**TTP**		
Audio Cond.	**V_i (km/h)**	**$D_{i.mov}$ (m)**	**Mean (%)**	**SD (%)**	**SE (%)**	**Mean (s)**	**SD (s)**	**SE (s)**	**Mean (s)**	**SD (s)**	**SE (s)**
No sound	20	25	27.30	30.80	5.63	1.28	0.56	0.06	3.43	0.54	0.06
		30	45.00	40.20	7.35	1.33	0.85	0.07	4.41	0.77	0.07
		35	53.00	40.40	7.37	1.37	0.89	0.07	5.19	0.81	0.06
	30	25	5.00	17.80	3.24	0.59	0.18	0.05	2.53	0.19	0.05
		30	9.33	22.70	4.15	0.81	0.39	0.07	2.95	0.31	0.06
		35	14.30	23.60	4.31	1.03	0.73	0.11	3.34	0.62	0.10
Sound	20	25	23.00	31.90	5.82	1.07	0.45	0.05	3.62	0.41	0.05
		30	41.30	42.30	7.73	1.18	0.58	0.05	4.53	0.52	0.05
		35	49.30	40.70	7.43	1.31	0.82	0.07	5.22	0.75	0.06
	30	25	4.33	16.80	3.06	0.69	0.19	0.05	2.41	0.23	0.06
		30	7.67	17.70	3.24	0.87	0.49	0.10	2.91	0.43	0.09
		35	12.70	22.90	4.18	1.05	0.50	0.08	3.32	0.43	0.07

4.3.1.1 Percentage of crossings

The percentage of crossings was examined using a three-way repeated-measures ANOVA with vehicle initial distance (3), vehicle speed (2) and the auditory condition (2) as factors. The auditory condition did not significantly influence the participants' percentage of crossings $F(1, 29) = 2.71$, $p = 0.11$, $\eta^2 = 0.09$. There was a main effect of vehicle speed, $F(1, 29) = 39.35$, $p < 0.01$, $\eta^2 = 0.58$, with higher values for the 20 km/h condition compared to when it was 30 km/h. There was also a main effect of vehicle initial distance, $F(2, 58) = 31.18$, $p < 0.01$, $\eta^2 = 0.52$, with Bonferroni post hoc tests showing that crossing percentages increased significantly with the initial distance. A significant speed × initial distance interaction was also found, $F(2, 58) = 9.66$, $p < 0.01$, $\eta^2 = 0.25$. Bonferroni post hoc tests were conducted comparing initial distances within each level of speed. At 20 km/h, there were significant differences between all levels of distance (25 m / 30 m: $p < 0.001$, 25 m / 35 m: $p < 0.001$, 30 m / 35 m: $p = 0.01$). At 30 km/h significant differences were only found between 25 and 35 m ($p < 0.001$).

In general, participants crossed more when vehicle speed was lower and its initial position was farther from the crosswalk. However, at 20 km/h, the distance increasing resulted in greater growth of the percentage of crossings (see Figure 4.6).

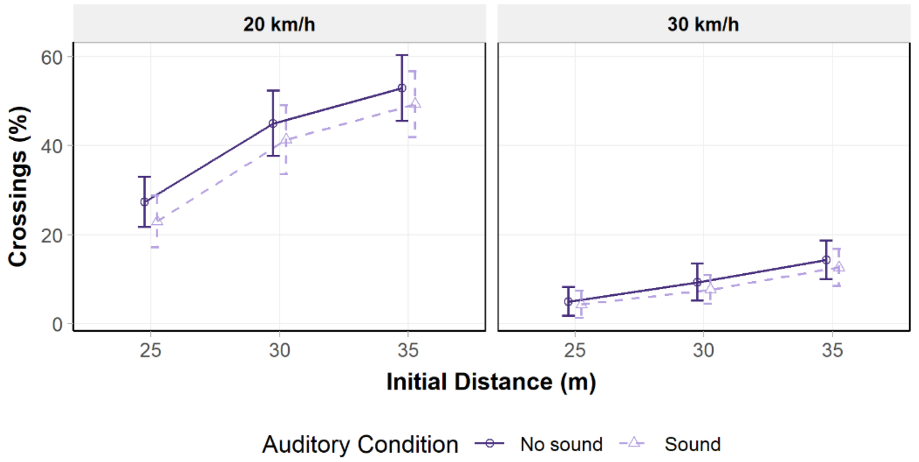


Figure 4.6 – Percentage of crossings and respective mean standard error as a function of auditory condition, per initial distance and initial speed (Constant speed pattern).

4.3.1.2 Response time

Initial analysis of response time data showed a skewness pattern typical of response times. A linear mixed model of response time with random effects included for *participant* and fixed effects defined for the *initial speed*, *speed pattern,* and *auditory condition* was fitted. Visual inspection of the residual plots showed deviations from homoscedasticity and skewness, so the model was refitted applying a logarithmic transformation to response times, which corrected the deviations. Satterthwaite's tests showed significant effects of vehicle initial speed, $F(1, 838.30) = 19.00$, $p < 0.001$, and vehicle initial distance, $F(1, 837.22) = 6.01$, $p < 0.05$, and an interaction between initial speed and initial distance, $F(1, 837.38) = 3.10$, $p = 0.04$. There was no effect of the auditory condition.

The model was refitted after discarding the auditory condition, and contrasts were used to analyse the interaction between vehicle initial speed and initial distance. Differences were found, for the initial speed of 30 km/h, between initial distances of 25 and 35 m, b = 0.20, t(842.84) = 2.45, p = 0.01. No significant differences were found for the speed of 20 km/h. Considering these results and Figure 4.7 that shows the response time as a function of vehicle initial distance, initial speed and auditory condition, it is apparent that participants' decisions to cross tended to be faster for higher speeds and when the vehicles were closer.

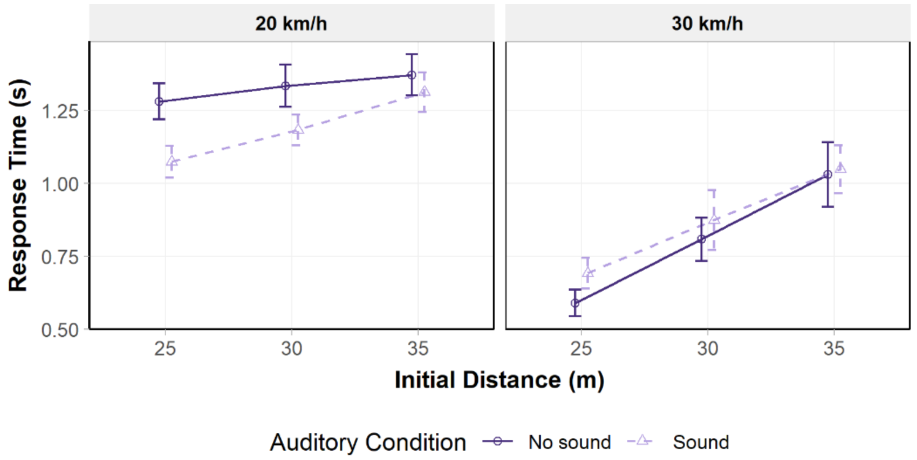


Figure 4.7 – Mean response time and respective standard error as a function of auditory condition, per initial distance and initial speed (Constant speed pattern).

4.3.1.3 Time-to-passage

Figure 4.8 shows the mean values of TTP at the crossing instant as a function of the TTP at the start of the trial. The observed TTP appears to vary linearly with the initial TTP. This was expected given that response time variations were small compared with the variation of initial TTP. The response time analysis done in the previous subsection showed that for those participants that crossed with the approaching vehicle at 30 km/h there was an attempt to compensate for the shorter available time by initiating the crossing earlier. However, TTPs were still lower than the ones observed at 20 km/h, meaning that participants who crossed at higher speeds were, in effect, taking riskier decisions.

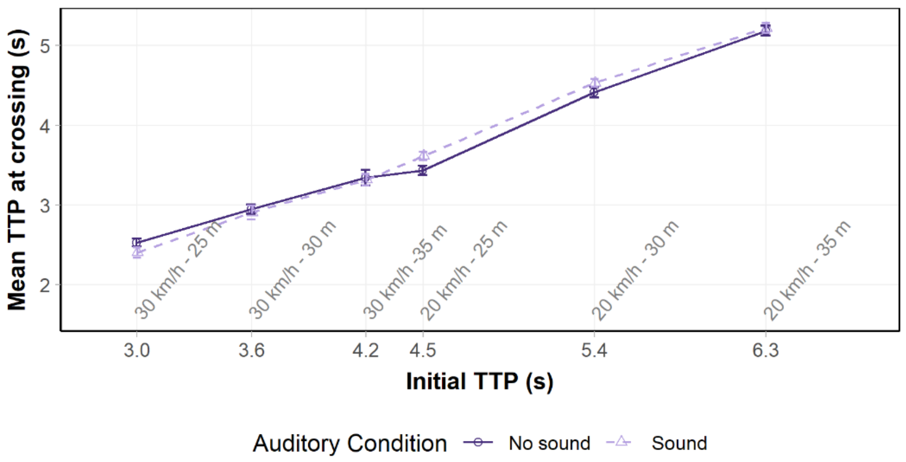


Figure 4.8 – Mean values of TTP at the crossing instant as a function of the TTP at the start of the trial (Constant speed pattern).

4.3.2 Different speed patterns

This section reports the analysis of participant's behaviour when confronted with different speed patterns. Figure 4.9 and Figure 4.10 show the crossings' data for each participant and condition (location of the circle along the axis represents the mean RT, the size of the circle represents the number of crossings, and the line shows the standard error of the mean; participants are vertically ordered according to mean RT). The line graphs show the actual speed profile observed by the participant (note that for the Constant speed profile, results are the same as in section 4.3.1.1 for the initial distance of 30 m).

The number of crossings increases substantially for the Slow Down and Stop patterns, particularly for those participants who crossed less times in the constant speed (Figure 4.9 and Figure 4.10). Nevertheless, these participants tended to cross later in the trial, when the vehicle was already slowing down.

The descriptive statistics of the results regarding the analysis of all speed patterns, in terms of percentage of crossings, RT, and TTP, are presented in Table 4.4.

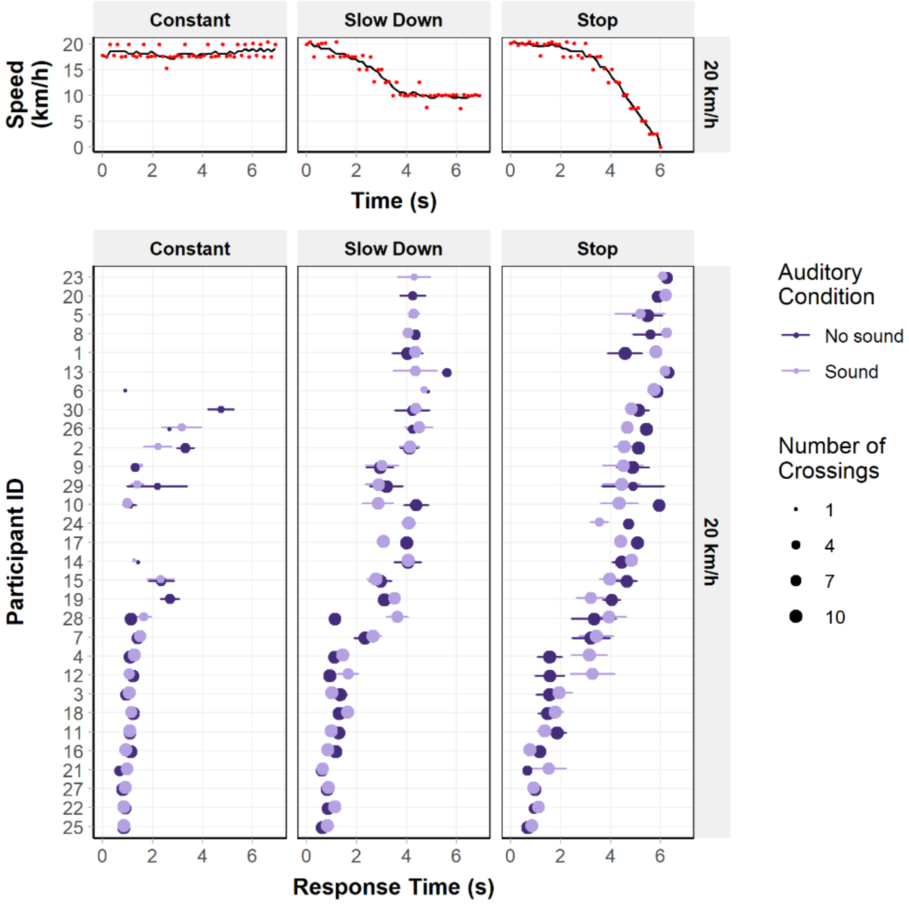


Figure 4.9 – Participants' responses and vehicle speed along time of stimulus' presentation, per speed pattern, for initial speed of 20 km/h.

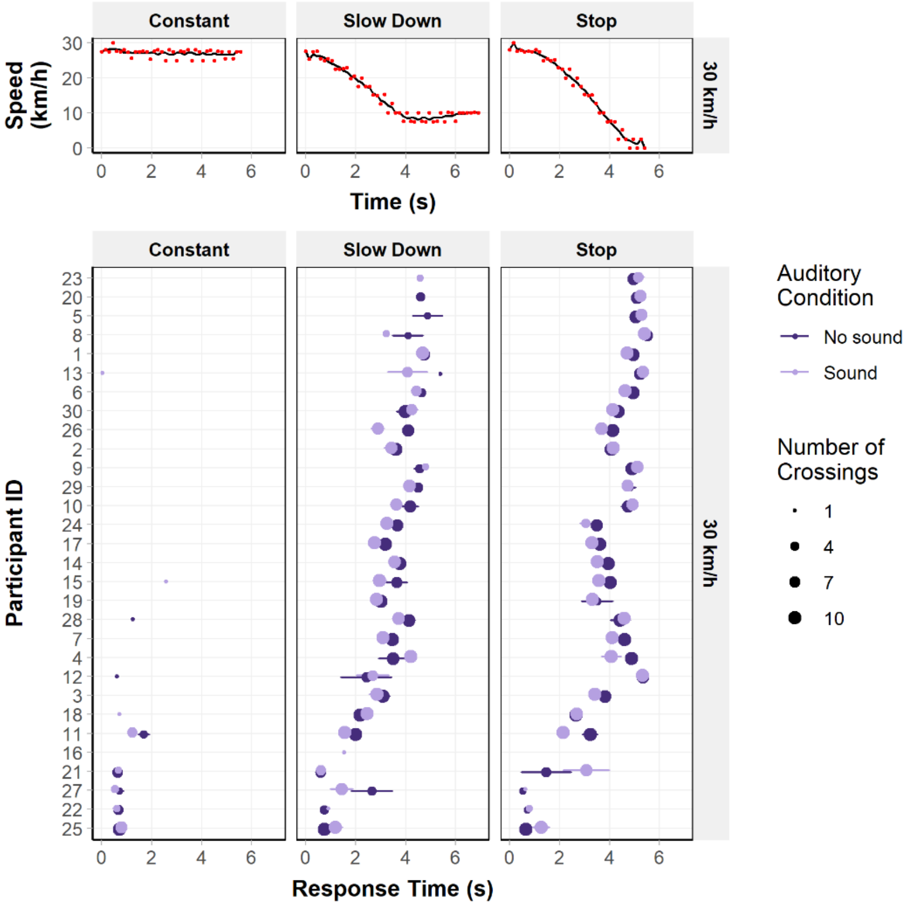


Figure 4.10 – Participants' responses and vehicle speed along time of stimulus' presentation, per speed pattern, for initial speed of 30 km/h.

Table 4.4 – Descriptive statistics of percentage of crossings, response time and TTP for each trial regarding all vehicle speed patterns.

			Crossings			Response time			TTP		
Audio Cond.	**V_i (km/h)**	**Speed Pattern**	**Mean (%)**	**SD (%)**	**SE (%)**	**Mean (s)**	**SD (s)**	**SE (s)**	**Mean (s)**	**SD (s)**	**SE (s)**
No sound	20	Constant	45.00	40.20	7.35	1.33	0.85	0.07	4.41	0.77	0.07
		Slow Down	74.30	33.30	6.08	2.45	1.73	0.12	4.17	0.67	0.04
		Stop	88.00	17.50	3.19	3.76	2.27	0.14	4.77	5.56	0.34
	30	Constant	9.33	22.70	4.15	0.81	0.39	0.07	2.95	0.31	0.06
		Slow Down	66.00	34.00	6.21	3.28	1.37	0.10	3.08	0.33	0.02
		Stop	78.70	30.30	5.52	4.10	1.31	0.09	7.92	12.60	0.82
Sound	20	Constant	41.30	42.30	7.73	1.18	0.58	0.05	4.53	0.52	0.05
		Slow Down	80.30	27.10	4.95	2.63	1.63	0.11	4.12	0.58	0.04
		Stop	87.70	17.90	3.28	3.64	2.19	0.14	4.68	6.07	0.37
	30	Constant	7.67	17.70	3.24	0.87	0.49	0.10	2.91	0.43	0.09
		Slow Down	69.00	35.60	6.49	3.10	1.24	0.09	3.06	0.33	0.02
		Stop	82.70	28.40	5.18	4.01	1.30	0.08	6.83	10.50	0.67

4.3.2.1 Percentage of crossings

Such as in the previous section, the percentage of crossings was examined in a three-way repeated-measures ANOVA. In this case, the *vehicle speed pattern*, the *initial speed*, and the *auditory condition* were the considered factors. Main effects were found for initial speed, F(1, 29) = 15.48, p < 0.001, η^2 = 0.35 and speed pattern, F(2, 58) = 68.16, p < 0.001, η^2 = 0.70, but not for the auditory condition F(1,29) = 0.70, p = 0.41. A significant initial speed × speed pattern interaction was also found F(2,58) = 14.72, p < 0.001. Bonferroni post hoc tests were conducted comparing the different speed profiles and initial speed within speed profiles. Generally, there was a significant increase in the percentage of crossings from Constant to Slow Down (p < 0.001) and from Constant to Stop (p < 0.001), but not from Slow Down to Stop (p = 0.09). Contrasts within each speed profile show differences between 20 km/h and 30 km/h for the Constant speed, t(60.50) = 6.38, p < 0.001, but not for the Slow Down, t(60.5) = 1.78, p = 0.08, nor the Stop, t(60.50) = 1.31, p = 0.19.

The results show that the participants crossed significantly more when the vehicle slowed down or stopped. They also show that the participants crossed more when the car was approaching at 20 km/h than at 30 km/h, but this difference was only significant when the car was approaching at constant speed. When the vehicle was slowing down, the speed played a substantially less important role in the participant's behaviour (see Figure 4.11 and Table 4.4).

These results indicate that for those conditions in which the vehicle speed varied, the participants had a greater tendency to cross after the speed began to decrease.

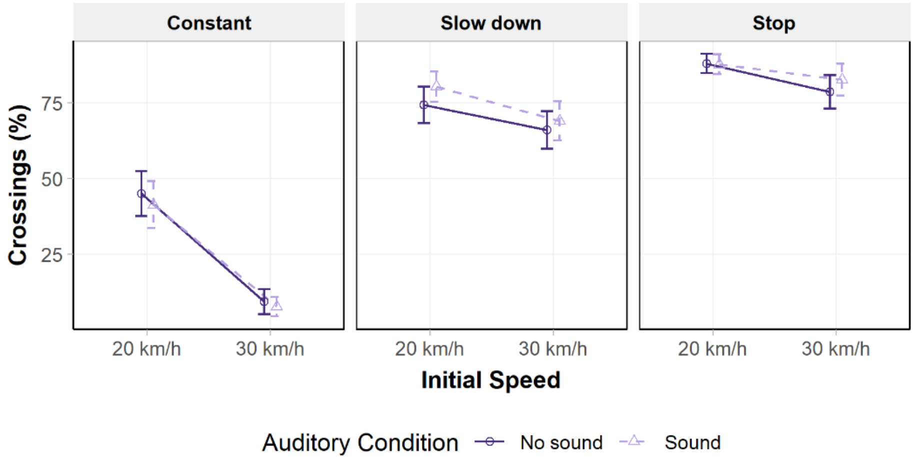


Figure 4.11 – Percentage of crossings and respective mean standard error as a function of auditory condition, per initial speed and speed pattern.

4.3.2.2 Response time

As in the previous section, a linear mixed model of log(Response time) with random effects included for *participant* and fixed effects defined for the *initial speed*, *speed pattern* and *auditory condition* was fitted. Visual inspection of the residual plots showed no deviations from homoscedasticity or skewness. Satterthwaite's tests showed significant effects of vehicle initial speed, F(1, 2151.10) = 25.72, $p < 0.001$, speed pattern, F(1, 2151.10) = 25.72, $p < 0.001$, and an interaction between initial speed and speed pattern, F(1, 2150.30) = 4.24, p = 0.01. There was no effect of the auditory condition.

The model was refitted after discarding the auditory factor, and contrasts were used to compare the different speed patterns. Differences were found between Constant and Slow Down patterns, b = - 0.24, t(2157.36) = - 5.94, p < 0.001, and between Slow Down and Stop, b = 0.24, t(2156.36) = 7.15, p < 0.001, indicating a significant increase in response time from Constant to Slow Down and also from Slow Down to Stop. A third contrast was used to compare the initial speeds of 20 km/h and 30 km/h for the Constant speed pattern compared to Slow Down. This contrast was significant, b = - 0.24, t(2157.08) = - 2.78, p < 0.01, meaning that for the Constant speed pattern, the value of response time decreased with speed, contrarily to Slow Down and Stop, in which response time increased with speed.

In the Constant speed profile, the crossing decisions were given at most until about 2.20 s after the stimulus started, for the stimuli characterized by a constant speed of 20 km/h, and up to about 1.20 s, for the ones with a constant speed of 30 km/h (Figure 4.12).

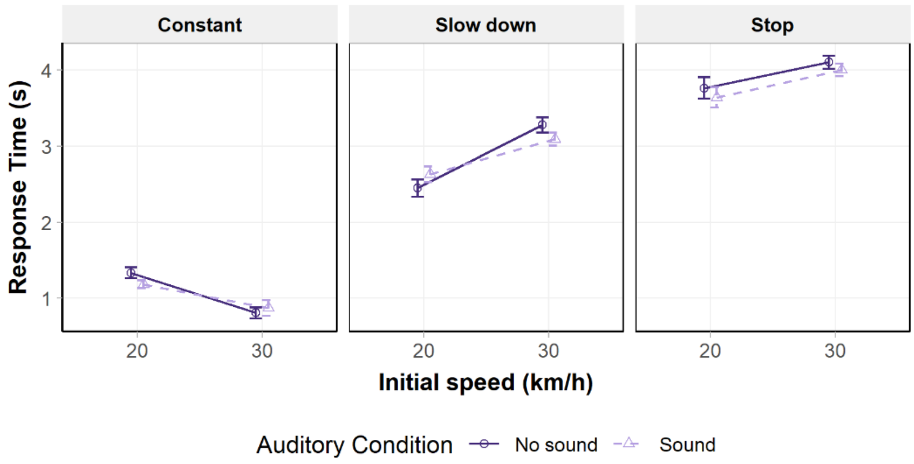
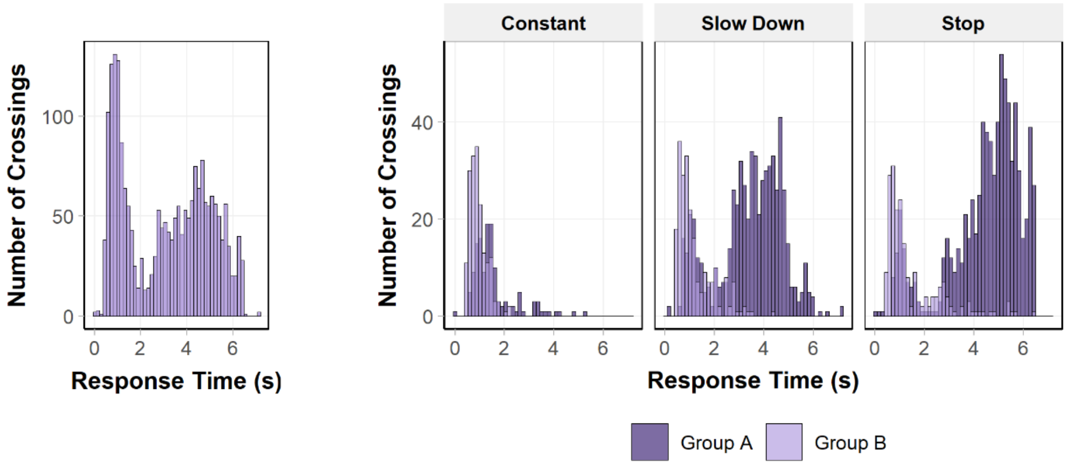


Figure 4.12 – Mean response time and respective standard error as a function of auditory condition, per initial speed and speed pattern.

Regarding the speed patterns in which the vehicle speed varied, the response time did not vary significantly between the different initial speeds, either in the Slow Down or in the Stop pattern. However, the values were considerably higher than those observed for the Constant speed stimuli. Nevertheless, a slight increase in the mean values of the response time is visible in the stimuli in which the movement of the vehicle started at a speed of 30 km/h.

Overall, the analysis of the percentage of crossings and the response time, shows that the participants crossed more often when confronted with the stopping and slowing down patterns. However, while some crossings happened during the initial moments of the stimulus presentation, as in the constant speed pattern stimuli, the others only took place after the vehicle began to slow down. Figure 4.13(a) shows the histogram of the number of crossings as a function of response time. One can see that most crossings concentrated around these two moments.

To verify if participants were individually consistent in the moments they choose to cross, the sample of thirty participants was split into two groups, according with the individual mean response times (Figure 4.13(b)). The value of 2.20 s was used as a threshold, since it corresponds to the local minima of the complete histogram that separates the early from the late crossings. One can see that response times above this threshold generally belong to the same participants, the ones who consistently crossed in the Slow Down and Stop conditions when the vehicle speed was decreasing (Group A). Response times below threshold belong to the other group (Group B) which includes those who tended to cross in the initial moments of the presentation of the stimuli, both at constant speed (especially at 20 km/h) and in the other conditions. The first group includes a major part of participants. A Mann-Withney confirms the observation, showing that the mean values of the response time of the two groups are statistically different (W = 945808, p-value < 0.01).



(a) (b)

Figure 4.13 – Histogram of number of crossings by response time: (a) for the general data; and (b) by speed pattern and group of participants.

4.3.2.3 Time-to-passage

A model was also fitted for TTP with random effect included for *participant* and fixed effects defined for the *vehicle initial speed*, *speed pattern,* and *auditory condition*. Visual inspection of the residual plots showed deviations from homoscedasticity and skewness. So, the model was refitted after applying a log transformation to TTP values, which minimized the deviations. As TTP is directly dependent on the response time, similar effects to the ones found on the response time model were expected to exist. Satterthwaite's tests showed significant effects of initial speed, $F(1,2152.80) = 61.11$, $p < 0.001$, speed pattern, $F(2,2157.30) = 3.05$, $p = 0.04$, and an interaction effect between initial speed and speed pattern, $F(2, 2151.20) = 39.27$, $p < 0.001$. There was no effect of the auditory condition.

The model was refitted discarding the auditory factor and contrasts were used to compare the different speed patterns. A first contrast compared the Constant and Slow Down speed patterns, and non-significant differences were found between them. A second contrast compared the Constant and Stop patterns, and it showed a significant difference between them, $b = -0.18$, $t(2163.03) = -5.07$, $p < 0.001$. A third contrast compared the Constant and Slow Down patterns for each initial speed. Significant differences were found, $b = 0.22$, $t(2158.82) = 2.91$, $p < 0.01$, showing that, for 20 km/h, the TTPs on the Slow Down pattern are significantly lower than in the Constant one, but for 30 km/h, the opposite is true. A fourth contrast showed the same tendency when comparing the Constant and Stop patterns for each initial speed. A significant difference was found, $b = 0.52$, $t(2158.61) = 6.86$, $p < 0.001$, showing that, at 20 km/h, the TTP was lower for the Stop compared with the Slow Down, but the opposite was true for the 30 km/h.

It is worth noting that, although the differences are significant, the TTPs for the Slow Down patterns are close to the ones for the Constant. Nevertheless, the percentage of crossing was remarkably higher in this condition, showing that participants have either made a substantially different risk assessment or were in the belief that, as the vehicle was slowing down it would eventually stop, which in fact did not happen. The large increase in TTP for the 30 km/h is shown in Figure 4.14. At 30 km/h, most crossings happened later in the trial, when the vehicle was already at a lower speed, making the TTP higher.

No significant differences were found for the auditory condition. However, Figure 4.14 shows that participants accepted higher TTPs when no sound was presented, particularly for the Stop pattern.

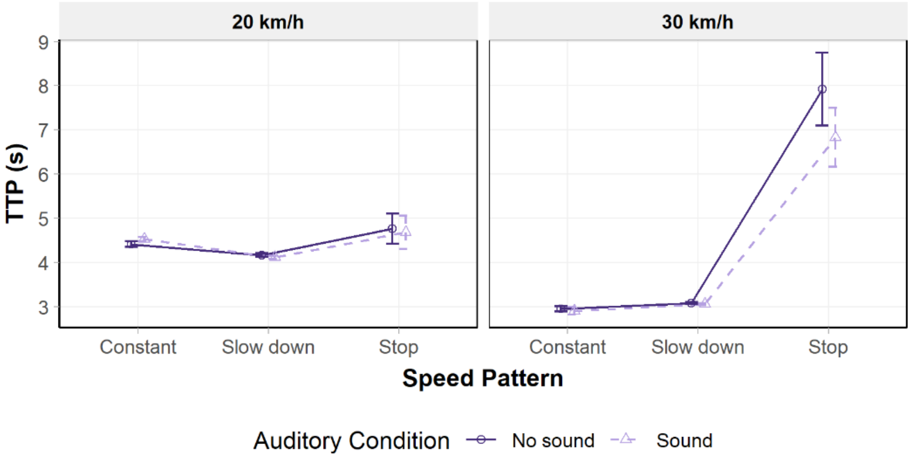


Figure 4.14 – Mean TTP and respective standard error as a function of auditory condition, per initial speed and speed pattern.

4.4. Discussion

For a vehicle approaching at constant speed, the results suggest that both speed and distance affect the crossing decisions. Crossing percentages increased with distance but were also substantially lower at the highest speed. While the experimental design used in this study does not allow a direct comparison of crossing decisions as a function of TTP with different speeds, the results do hint to an important role of speed in crossing decisions instead of a decision criterion based mostly on distance. Considering that the study population was composed of young adults, with ages between 20 and 40 years old, this agrees with past research (e.g. (Liu and Tung, 2014; Lobjois and Cavallo, 2007, 2009; Oxley *et al.*, 2005)) which indicates that young people are better at estimating the available time to cross and thus more apt to balance the risk of increased speed. However, these results contrast with the study of Feldstein and Dyszak (2020). In their experiment, a group of young participants seemed to use distance-based criterium in a virtual environment in contrast to a time-based criterium in real environment. The difference might be attributed to different experimental speeds. It is known that lower speeds are easier to distinguish. The virtual vehicle used by Feldstein and Dyszak (2020) moved at speeds ranging from 30 to 40 km/h. In this study, speeds between 20 and 30 km/h were used, which may have made the lower speed more salient in comparison to the higher, fostering a weighted crossing decision.

The response times also showed dependency on both speed and distance. Higher speeds and shorter distances seem to have prompted faster decisions, although this result was only significant for the higher speed. This observation was not entirely unexpected. Lobjois and Cavallo (2009) compared response times for crossing decisions in a simulated environment, with and without a time constraint. They verified that participants were faster to respond under the time-constrained condition, which also favoured a distance-based decision. It is possible that, in this study, the higher speeds and close distances have prompted a similar sense of urgency, which is known to accelerate decision processes, although at the cost of accuracy in judgments (Soares *et al.*, 2020). This agrees with Beggiato *et al.* (2018), who analysed the effect of daytime, approaching vehicle speed and pedestrian's age on the time gaps accepted to cross the road, and found that the participants took more risky crossing decisions, accepting lower time gaps with the increasing vehicle speed.

An important consideration can be made regarding the individual subjects' behaviour. It is noticeable that most participants were consistent in terms of response time and crossings percentages but differed substantially among themselves. Participants with higher crossing percentages were also the ones with shorter response times. Figure 5 shows that participants who decided not to cross at 30 km/h crossed fewer times and did so later at 20 km/h. In contrast, participants who decided to cross often at 30 km/h also decided to cross early for both approaching speeds, pointing to a more impulsive behaviour. However, the faster responses were not enough to substantially increase the TTP, which means that in a real situation, these participants would had put themselves at greater risk.

Concerning the influence of the auditory condition on participants' crossing decision, despite a slight superiority in the crossing percentages obtained in the presentation of the merely visual stimuli, mainly for the speed of 20 km/h, the applied statistical tests showed that differences were not significant. The analysis of the response time and, consequently, TTP made it even more evident that the auditory condition had no effect on the participants' crossing decision-making.

Regarding the comparison between different types of speed pattern, results also showed a significant influence of the vehicle's initial speed on the percentage of crossings. In this case, the participants crossed more often when the initial speed of the vehicle was 20 km/h. The analysis of the results showed even more clearly a division between those participants who crossed shortly after the start of the stimulus and those who took more time to decide. As previously referred, participants with shorter reaction times tended to cross more often, showing that they are more likely to make dangerous decisions consistently. Most of the participants took a more cautious approach, with few crossings when the vehicle was approaching at a constant speed, particularly at 30 km/h. When the vehicle slowed down, they started to cross when the speed started decreasing. The longest response times in the Stop and Slow Down conditions confirm this behaviour.

For both conditions, participants seem to have assumed that the deceleration meant the vehicle would stop, or at least provide them enough time to cross, irrespective of the initial speed. An indication of this can be found in the differences in the percentage of crossings between initial speeds. In the Constant speed condition, this difference is substantial with more crossings at 20 km/h. In the Slow Down and Stop conditions there is no significant difference between initial speeds. Also, crossing percentages are overall higher than in the Constant condition. The TTP analysis also seems to support this. At the initial speed of 30 km/h in the slow down condition, the TTP was remarkably lower than in the stop condition, although neither response time nor crossing percentages differed significantly. This again seems to indicate that participants made their decisions based on the perceived deceleration and not on a TTP estimation.

The results highlight the role of perceived vehicle kinematics as a communication tool between vehicle and pedestrian. The early deceleration seems to have been taken by the participants as an indication that they could cross, with the initial speed and actual driver intention (stop or simply slow down) playing a less important role in the decision. This conclusion is in line with the results of recent studies that explore the role of vehicle movement as a mean of communication and coordination between drivers and pedestrians. Deceleration is normally interpreted by pedestrians as an indication that the driver has seen them and will yield the passage (Ackermann *et al.*, 2018; Dey *et al.*, 2019; Mahadevan *et al.*, 2018; Schmidt and Färber, 2009; Várhelyi, 1998). Drivers, in turn, may deliberately use anticipated braking as a way to signal their yielding intention, encouraging the pedestrian to cross with the vehicle still moving, speeding up the encounter and eventually preventing the need for a full stop (Risto *et al.*, 2017).

This result has implications in the development of communication strategies between automated vehicles and pedestrians, a topic that has been receiving growing attention as the presence of driverless vehicles in our roads seems to be an approaching reality (Schneemann and Gohl, 2016; Sucha *et al.*, 2017). On the one hand, vehicle developers should keep in mind that speed adjustments may convey false cues regarding vehicle behaviour. On the other hand, kinematics may be a simple way to convey intention to pedestrians, although it should also be considered that judgements of available crossing time may be inaccurate and lead to risky situations (Dietrich *et al.*, 2020).

At last, regarding the audio-visual and the merely visual stimuli, participants relied mostly on the visual information they received from the approaching vehicle to estimate the available crossing time, contradicting Barton *et al.* (2012) and agreeing with the conclusions of Pugliese *et al.* (2020) and Soares *et al.* (2020). These results prove that the absence of the audio component regarding the road traffic does not compromise the results obtained in pedestrian safety studies performed in a virtual environment. Table 4.5 summarizes the main findings of the present work.

As a limitation, it should be underlined that this study only considers the particular situation in which the vehicle approached the pedestrian from a clearly visible position and maintaining a straight trajectory without obstacles to the participants' view, such as in other studies developed in this research area (e.g. (Cavallo *et al.*, 2019; Cavallo *et al.*, 2009; Charron *et al.*, 2012; de Clercq *et al.*, 2019; Dommes *et al.*, 2012; Feldstein *et al.*, 2016; Simpson *et al.*, 2003; Zito *et al.*, 2015)). In cases in which the visibility of participants could be impaired, greater importance of the auditory cues in their decision would be expected, as shown by Barton *et al.* (2012).

Another limitation of this study was the participants' experimental task. In the experiments, participants signalled their decision by clicking on a button of a computer mouse while remaining still in a predetermined position. This approach has been used in most pedestrian simulator studies (Charron et al., 2012; Meir et al., 2015; Schwebel et al., 2008; Thomson et al., 2005; Zito et al., 2015). Some of the most recently developed simulators already allow participants to freely walk the virtual crossroad (Cavallo *et al.*, 2019; Deb *et al.*, 2018b; Feldstein *et al.*, 2016; Morrongiello *et al.*, 2015; Schneider *et al.*, 2021; Simpson *et al.*, 2003; Sween *et al.*, 2017). Being able to move freely turns the simulator and the experimental task more realistic and immersive. It provides participants with a complete sense of the space and their own speed and, consequently, of the time they need to initiate movement and cross the road. However, one of the objectives of this study was to analyse the role of auditory cues in the pedestrians' crossing decision and modelling vehicular sound in a spatially congruent manner for a moving listener is far from trivial. For the sake of simplicity, it was decided to consider an experimental task where the participant chose between go/no go options by clicking on a simple button. This also allowed for lighter and less time-consuming trials for the participants.

Table 4.5 – Summary of the main findings.

Main Findings	Agreeing with	Disagreeing with
When a vehicle is approaching the crosswalk at constant speed, both speed and distance affect the pedestrian crossing decisions.	Oxley *et al.* (2005); Lobjois and Cavallo (2007); Lobjois and Cavallo (2009); Liu and Tung (2014)	Feldstein and Dyszak (2020)
Vehicle's higher speeds and shorter distances lead to faster and unsafe crossing decisions.	Lobjois and Cavallo (2009); Beggiato *et al.* (2018); Soares *et al.* (2020)	-
Assuming full visibility of the approaching vehicle, the auditory condition does not influence the pedestrians' crossing decision-making.	Pugliese *et al.* (2020); Soares *et al.* (2020)	Barton *et al.* (2012)
Vehicle kinematics is a relevant communication tool between vehicle and pedestrian. Vehicle deceleration is interpreted by pedestrians as an indication of the intention to yield the passage.	Várhelyi (1998); Schmidt and Färber (2009); Ackermann *et al.* (2018); Mahadevan *et al.* (2018); Dey *et al.* (2019)	-

Future work may pass by the analysis of other types of trajectories (such as turning movements at intersections) and obstacles to the participants' vision (such as parked vehicles, trees, and urban furniture), to assess the general effect of the auditory cues on the pedestrian crossing decision-making in a more comprehensive way.

4.5. Conclusions

The main goal of this research was to analyse the role of visual and auditory cues in crossing decisions, considering different initial speeds and distances of the vehicle as well as deceleration profiles. The results support the general conclusion that the speed and initial distance of the vehicle and its speed profile impact the crossing behaviour. Contrarily, the auditory input has no major role in modulating decisions, at least when pedestrians are crossing a virtual road having perfect visibility conditions of the approaching vehicle.

Regarding the vehicle motion, most participants made a decision based on the vehicle's perceived kinematics, with the deceleration being interpreted as an indication that the vehicle would yield the passage. However, a small group of participants seems to have responded more hastily, taking less time to decide, crossing more often, including when the vehicle approached at the highest speed and from closer distances and irrespective of whether it would yield or not.

These conclusions highlight the role of vehicle kinematics as an important mean of communication between vehicles and pedestrians, which should be considered in the development of new strategies to mitigate the severity of conflicts between vulnerable road users and motorized traffic. The results are also relevant for autonomous driving developers, showing that vehicle movement can be explicitly used to communicate with pedestrians and that care should be taken to prevent unintentional, misleading signals.

5. COMPARISON BETWEEN TWO TYPES OF EXPERIMENTAL APPROACH TO ASSESS THE PEDESTRIAN BEHAVIOUR IN VIRTUAL ENVIRONMENT

5.1. Introduction

As previously referred, understanding which variables may influence the pedestrian behaviour and decision-making during conflicts with the motorized traffic, such as crossing the road, has been the goal of several studies over last years (*e.g.* (Bernhoft and Carstensen, 2008; Ewing and Dumbaugh, 2009; Ezzati Amini *et al.*, 2019; Granié *et al.*, 2014; Hamed, 2001; Holland and Hill, 2007; Ishaque and Noland, 2008; Johansson *et al.*, 2004; LaScala *et al.*, 2000; Leden, 2002; Lin *et al.*, 2015; Moyano Díaz, 2002; Oxley *et al.*, 2005; Papadimitriou *et al.*, 2016a, 2016b, 2017; Papadimitriou *et al.*, 2012; Rosenbloom *et al.*, 2008; Sucha *et al.*, 2017; Sueur *et al.*, 2013; Turner *et al.*, 2006; Zegeer *et al.*, 2006)).

As mentioned in Chapter 1 and according to Papadimitriou *et al.* (2016b), Feng *et al.* (2021), and Deb *et al.* (2018a), methods for analysing pedestrian behaviour are based on field observation, survey, semi-controlled experiments, and simulation.

The most common way of gathering data about pedestrians' crossing behaviour is through video recordings of those same pedestrians (Lassarre *et al.*, 2012). Those recordings, however, are limited to the used camera's field of vision and may fail to capture important parts of the interaction. Other alternatives, such as following the trajectory of pedestrians through GPS instruments or Bluetooth/Wi-Fi sensors, have also limitations, such as problems with precise location and unavailability of information regarding traffic conditions (Feng *et al.*, 2021; Papadimitriou *et al.*, 2016a).

Surveys are the most often used method to obtain data for qualitative analysis. They are done through written documents, online questionnaires, face-to-face or telephone interviews (Deb *et al.*, 2018a). However, participants' answers may not portray their actions in real situations, and a big sample of participants is demanded (Feng *et al.*, 2021).

Semi-controlled experiments are usually applied to analyse factors such as gait parameters and pedestrian spatial organization along predefined paths (Cao *et al.*, 2018; Fu *et al.*, 2019; Wei *et al.*, 2015). However, this method has the same limitation as all pedestrian controlled experimental studies. The participants' behaviour can be influenced by the fact they know they are being observed and analysed.

Alternatively, some experiments have been performed using virtual reality simulators in which the test participant visualizes a crossing situation and must choose between go/no got options throughout clicking a simple button (Charron *et al.*, 2012; Meir *et al.*, 2015; Schwebel *et al.*, 2008; Thomson *et al.*, 2005; Zito *et al.*, 2015) or having a free walk on a virtual crosswalk (Cavallo *et al.*, 2019; Deb *et al.*, 2018b; Feldstein *et al.*, 2016; Morrongiello *et al.*, 2015; Simpson *et al.*, 2003; Sween *et al.*, 2017).

Despite having disadvantages such as the greater need for space to carry out the experiments and dependence on expensive equipment, simulator-based experiments for studying road agents' behaviour have several advantages compared with similar experiments conducted in real-world. They avoid most of the hurdles required to ensure participants' safety in real environments while allowing more control over experimental conditions and tasks (Deb *et al.*, 2017).

Pedestrian crossing simulators can be divided into simulators that rely on head-mounted displays (HMDs) or simulators that use Cave Automatic Virtual Environments (CAVE) technology (Cavallo *et al.*, 2019). Compared to HMD solutions, projection-based simulators allow for greater freedom of movement for the participants. By using a power-wall configuration and a motion tracking system to project the intended scenario with a perspective adjusted to the physical location of the participant, this type of simulators allows participants to conduct the act of crossing on their own, without the use of instruments such as treadmills or joysticks (Cavallo *et al.*, 2019).

Pedestrians' behaviour must be studied with enhanced tools to provide a complete and reliable tool for road safety managers. According to Feldstein *et al.* (2016), the quality of each simulator is associated with the capacity of inducing on the participants the feeling of being present in the virtual environment and not just perceiving it as a digital image, which in turn depends on the realism of the environment and the usability of the simulator, supported by the quality of the graphical representation, sound, and interaction possibilities.

Like the sound, the fact that participants can move freely turns the simulator more realistic and immersive. Still, it is not known if this has a measurable impact on participants' decision-making. If the effect of the auditory cues on the participants' decision was addressed in Chapter 3 and Chapter 4, the importance of participants' free movement in their decision-making should also be assessed. The work reported in this chapter aimed to evaluate the effects of a more realistic approach for studying pedestrian crossing behaviour using a perception-action task in which the participants were required to walk effectively along a semi-virtual crosswalk.

Taking advantage of the ability of the CAVE system to truly isolate the users from the real world and involve them in a traffic environment (Deb *et al.*, 2017), a comparison was done between the results of the experiment reported in chapter 4 (static crossing evaluation condition) and a new experiment in which a different group of participants was confronted with a dynamic crossing evaluation condition, in which the crossing decision was done while walking along the virtual crosswalk.

5.2. Materials and Methods

5.2.1 Participants

A sample of 30 adults was recruited from the University of Minho community, in Portugal. These participants performed an experiment under the dynamic crossing evaluation condition. As mentioned above the data gathered from the study described in Chapter 4 was also used for the data analysis in this chapter (Chapter 5), since its aim was to compare two experimental approaches: the static approach, which was used in the experiment described in Chapter 4, and the dynamic approach. In this way, the complete sample had 60 participants. For comparison purposes, the details about the demographic characteristics of the two groups of participants are presented in Table 5.1.

Following the methods of the previous study, before the experiment, all participants answered a questionnaire regarding their hearing, visual, and mobility conditions. None of them reported any impairing condition. All participants gave their written informed consent. The experiments were conducted following the principles stated in the 1964 Declaration of Helsinki.

Table 5.1 – Participants' demographic characteristics.

	Experimental Approach		
	Static	Dynamic	Total
Age	24-60 years (m = 39.70; sd = 12.11)	23-57 years (m = 39.17; sd = 10.44)	23-60 years (m = 39.88; sd = 11.20)
Sex	46 % Male; 54 % Female	57 % Male; 43 % Female	52 % Male; 48 % Female

5.2.2 Virtual environment

The same two virtual scenarios of the previous experimental studies presented in Chapter 3 and Chapter 0, 25A and TP streets (see Figure 3.1, Figure 4.1, and Figure 4.2), were used in this study.

The method to model the vehicle's movement was also the same used in the studies in the virtual environment presented in the two previous chapters. It involved the use of the data collected with the analysis of the 2 hours video recorded in each one of the streets modelled, clustering the trajectories and speeds into three distinct categories: (i) Constant Speed; (ii) Slow Down; and (iii) Stop, and defining the characteristics of the movement of the virtual vehicle. The ten conditions considered in this study were the same depicted in Chapter 4 (see Table 4.2).

Regarding the sounds presented in the experiments, as previously referred, in the static approach, the vehicle emitted the sounds acquired through the CPB measurements of the approaching of a Kia Ceed SW, with a gasoline combustion engine, equipped with ContiEcoContact3 195/65-R15 tires, performed with a Brüel & Kjaer Pulse Analyzer type 3560-C and a Brüel & Kjaer Head and Torso Simulator (HATS) Type 4128-C equipped with Ear Simulators Type 4158-C and 4159-C which the detailed information is presented in section 4.2.3.2.

Table 5.2 presents the main characteristics of the stimuli audio component of the static experimental approach.

Table 5.2 – Acoustic characteristics of the stimuli regarding the static approach (CPB sounds).

	Condition									
Indicator[1]	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
LAeq (dB(A))	66.22	65.67	65.23	71.09	70.58	70.19	58.59	60.04	58.90	61.04
LAmax (dB(A))	72.81	72.81	72.81	77.49	77.49	77.49	61.12	64.28	63.93	66.15
L5 (dB(A))	72.27	72.08	71.85	76.88	76.83	76.77	60.70	63.74	63.40	65.46
L10 (dB(A))	71.09	70.68	70.28	76.19	75.75	75.31	60.43	63.45	62.75	63.93
L50 (dB(A))	62.72	61.89	60.98	67.67	66.93	65.85	58.17	57.34	57.89	60.52
L90 (dB(A))	57.81	57.32	56.12	60.09	60.28	59.97	56.42	56.06	52.80	52.65
Measurement time (s)	6.45	7.50	8.40	4.80	5.55	6.15	7.50	7.05	10.20	9.30
Dynamic range (dB(A))	28.15	28.15	28.15	32.83	32.83	32.83	16.46	19.62	19.27	21.50

[1] values of the acoustic indicators for the sound acquired by the HATS's left channel (left ear).

In the dynamic approach, the vehicle emitted auralized sounds acquired through the Close Proximity (CPX) measurements. The CPX acquisitions were simultaneously performed to the CPB ones. The mentioned vehicle was instrumented with two Brüel & Kjaer microphones type 4189 mounted on the back-right wheel and linked to the Brüel & Kjaer Pulse Analyzer type 3560-C with an arrangement in accordance with the EN ISO 11819-2 (2017) descriptions. The signal captured by the CPX microphones is predominantly tyre-road noise.

The sounds recorded through the CPX method were submitted to an auralization routine that outputs corresponding binaural CPB-like samples. This allowed a subject to hear a sound that appeared to come from the approaching vehicle (that was being observed in the projection screen).

The auralization routine of the CPX captured signal consisted of the analytical formulation of a transfer function having as input a mono signal and as output a propagated equivalent binaural signal at an arbitrary far-field point. Its' determination was grounded on the propagation filter developed by Anfosso-Lédée (2004), that related near-field captured CPX signals to corresponding sound pressures at a point in the far-field (at the CPB location). It firstly characterized a tyre-road noise equivalent source position and power, then determined the attenuations imparted by the propagation effects to a far field position. The developed auralization routine considered then, source characteristics, environmental conditions, direct and ground reflections propagation paths, ground surface characteristics and finally, Head Related

Transfer Functions (HRTFs). The resulting output was an auditory binaural signal plausibly perceived as one emitted by a real vehicle for an arbitrary far-field listener position, which was applied to simulate the noise emitted by a virtual vehicle approaching a crosswalk. For a detailed information about the auralization of the CPX sounds see (Pereira *et al.*, 2021).

The auralization routine was implemented in Cycling74 Max/Msp environment paired with the BlenderVR add-on (Katz *et al.*, 2015). Based on the spatial location of the sound source and listener, the algorithm performed real-time attenuation of a monaural signal, replicating effects of air absorption, ground reflections and temperature gradients and sound energy loss to other surfaces. The Max patch used the Ircam's Spat (Carpentier, 2018) patch for audio spatialization of the source signal. The binaural signals' directional auditory cues were obtained from real-time convolution of the monaural CPX recording with the corresponding direction of arrival HRTFs. A schematic representation of the auralization routine is presented in Figure 5.1.

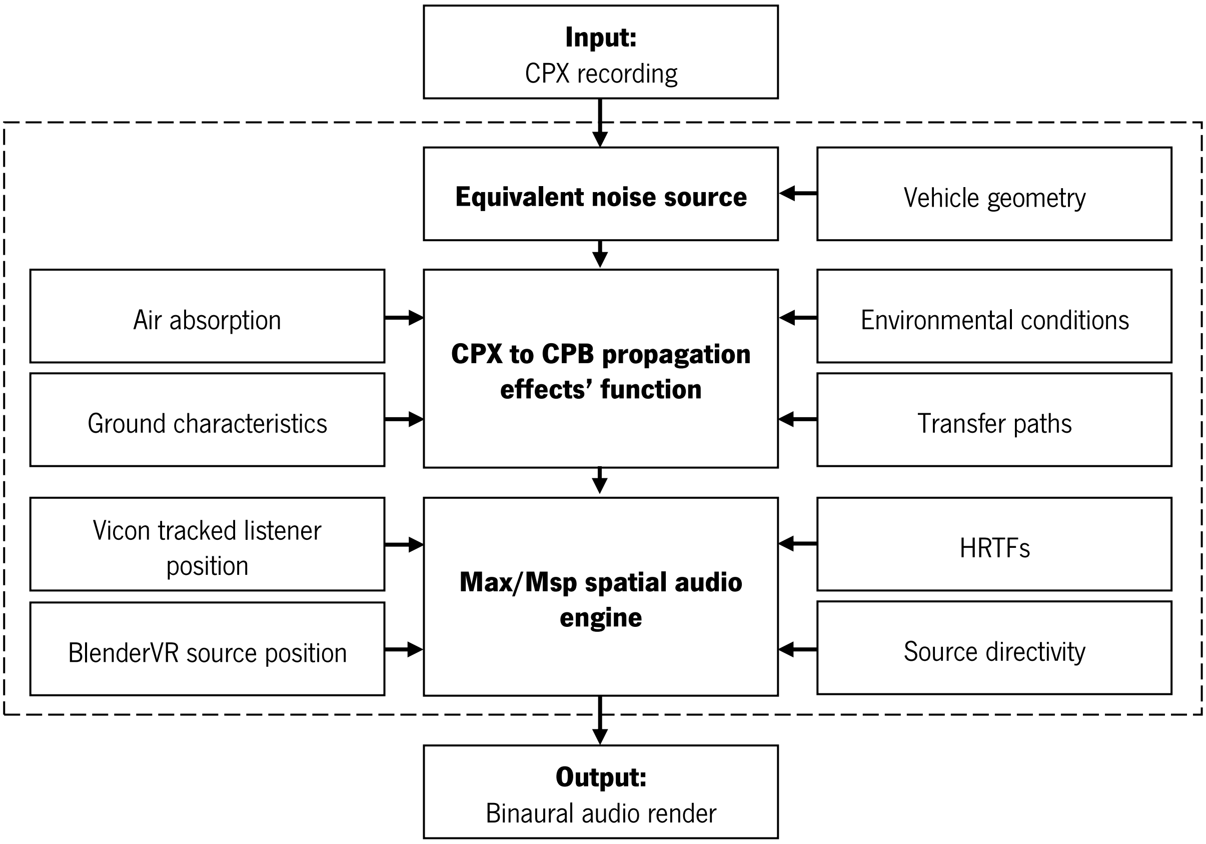


Figure 5.1 – Schematic representation of the auralization routine.

The listener position and orientation within the simulator was, in the case of this study, tracked by a Vicon MoCap system and sent through the BlenderVr add-on to a Max spatial audio processor. Source coordinates were sent from a Blender "virtual world" model, incorporating an animated vehicle trajectory. The auralization routine reacts dynamically to receiver motion and head orientation.

Table 5.3 presents the main characteristics of the stimuli audio component of static experimental approach. Comparing the values of the acoustic indicators of CPX auralized sounds (Table 5.3) with those regarding the CPB recordings (Table 5.2) the differences observed are very small, validating the auralized sound samples exported by the routine previously described.

Table 5.3 – Acoustic characteristics of the stimuli regarding the dynamic approach (CPX auralized sounds).

	Condition									
Indicator[1]	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
LAeq (dB(A))	66.35	65.75	65.32	71.07	70.49	70.10	58.80	61.64	59.15	62.49
LAmax (dB(A))	72.70	72.67	72.89	78.16	78.03	77.71	62.03	65.83	63.32	66.34
L5 (dB(A))	71.68	71.81	71.77	77.16	76.93	76.60	61.65	65.17	62.91	65.65
L10 (dB(A))	70.56	70.74	70.33	75.83	75.38	75.05	61.26	64.95	62.15	65.48
L50 (dB(A))	62.54	62.65	61.39	67.82	66.61	66.03	58.90	61.71	58.75	62.13
L90 (dB(A))	57.27	56.98	55.65	61.15	60.96	60.76	51.37	50.47	55.21	55.73
Measurement time (s)	6.45	7.50	8.40	4.80	5.55	6.15	7.5	7.05	10.20	9.30
Dynamic range (dB(A))	25.47	25.44	25.66	30.93	30.80	30.48	14.80	18.60	16.09	19.11

[1] values of the acoustic indicators for the sound acquired by the channel (left ear).

5.2.3 Stimuli

The same visual stimuli were presented to both groups of participants, changing only the auditory ones. The ten conditions shown in Table 4.2 were repeated five times for each participant. In total, throughout the experiment, 100 stimuli were presented in a random order (10 movement conditions × 5 repetitions × 2 streets). The virtual model of the approaching vehicle used in the experiment was the Kia Ceed SW (Figure 5.2).

Figure 5.2 – Visual model of the vehicle used in the experiment.

5.2.4 Instruments

The experiment was conducted in the same room and using the same CAVE type system used in the studies described in the two previous chapters (see section 3.2.4 of Chapter 3).

CPB and CPX auralized sounds were played synchronously with the corresponding visual stimuli on the headphones in static and dynamic approaches, respectively, using VLC media player. In both approaches, the sound was amplified through a Sony TA-AV570 Audio Video Amplifier. Acoustic levels were calibrated to ensure they were equal to the ones registered during the recording sessions.

5.2.5 Experimental procedure

In the dynamic approach, each participant was placed in a predefined point of the room where they had to start the experiment. The visual scene was rotated 45° with the screen. Participants were asked to put on the headset and the 3D glasses while listening to the instructions and tasked with instructions to walk along a predefined circuit around the CAVE room and cross the virtual crosswalk when they felt safe to do so. If they did not decide to cross during a trial, they were told to wait on the curb for the vehicle to pass by them and then to walk again to complete the circuit, into the next trial. Each stimulus was presented when the participant was 3 m far from the curb (see Figure 5.3). Figure 5.4 shows an example of the performance of the dynamic experiment.

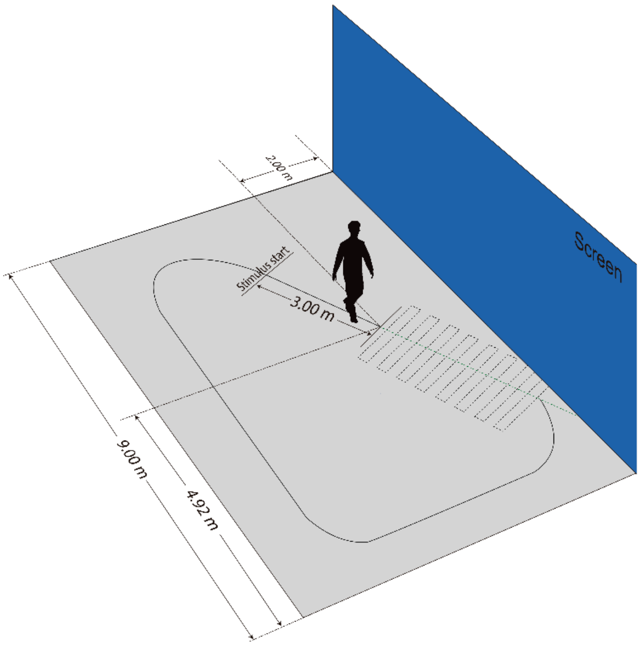


Figure 5.3 – Spatial layout of the room in the dynamic approach.

Figure 5.4 – Participant performing the dynamic experiment.

As in the other experiments, participants completed an experimental session made of two main blocks, one using the 25A scenario and others using the TP scenario, preceded by a training block composed of 4 stimuli. There was a gap of 5 minutes or more between the two main blocks to rest, depending on the participant's wishes.

5.2.6 Analysis

The influence of the several variables addressed in this study on the participants' crossing decision-making was analysed in terms of the percentage of crossings, crossing start time, and TTP.

Such as in Chapter 3 and Chapter 4, the percentage of crossings was calculated, for each participant, by assuming that: (i) in static approach, a decision to cross was considered in the trials in which the computer mouse was clicked before the vehicle had stopped or passed by the participants' position; and, (ii) in dynamic approach, a decision to cross was considered in the trials in which the participants had crossed the half-length of the semi-virtual crosswalk before the vehicle had stopped or passed in front of them. Since the participants' task was to effectively cross the virtual road, in the dynamic approach (contrary to the static approach) it was possible to count the number of crashes. The crossing start time, corresponding to the time from the beginning of the stimulus presentation until the moment when the participant clicked the mouse or took the first step on the crosswalk, was also registered.

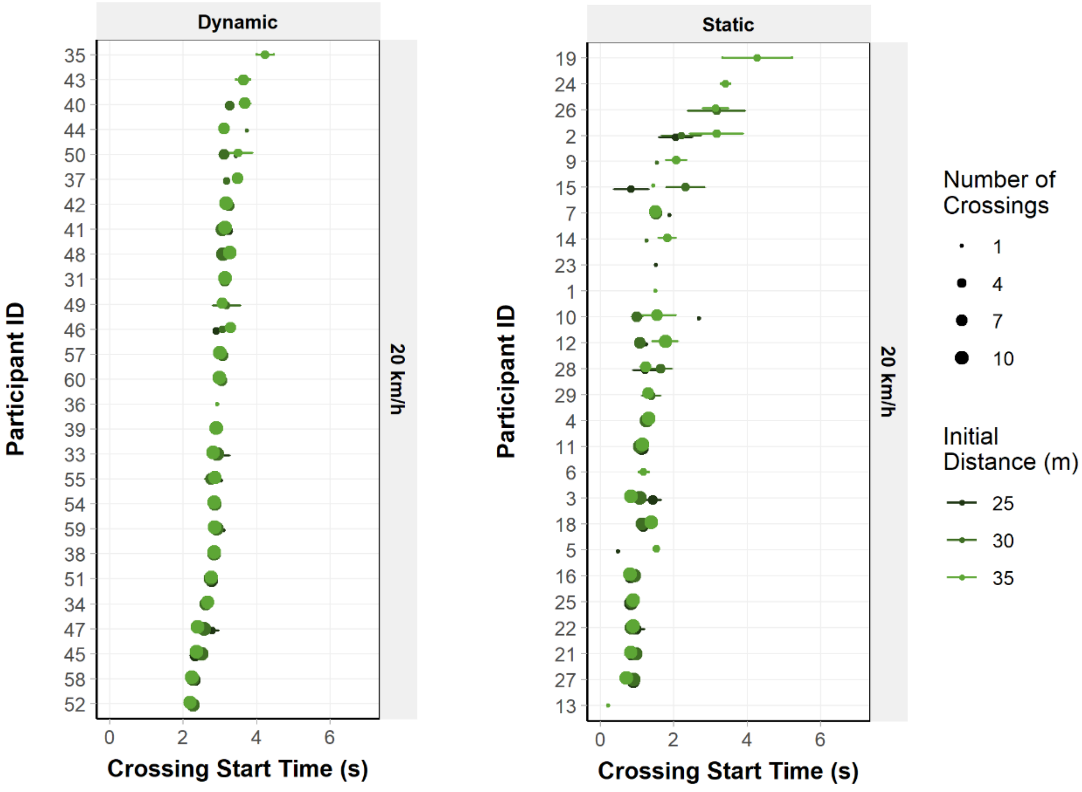
The influence of the variables *experimental approach*, *vehicle speed pattern*, *vehicle initial speed*, and *vehicle initial distance* on the percentage of crossings was assessed using a three-way repeated measures ANOVA. The *crossing start time* and *TTP* were assessed by fitting mixed-effects regression models with random effects included for the participant and fixed effects defined for the three variables mentioned above. The use of LMMs is justified by the existence of missing values in the data, corresponding to trials in which participants did not cross.

The analysis of the results was done in two stages: in the first stage, the conditions characterized by Constant speed patterns are analysed, since, only in these cases, there was a variation of the vehicle initial distance; In the second stage, the data regarding all speed patterns is analysed considering only the conditions with 30 m of initial distance for the Constant speed trials. In this way, it was ensured that the analysis of the vehicles' speed patterns effect on the participants' responses was carried out under equal conditions. Complementarily, a comparison between the TTP obtained with the two experimental approaches' performance and the video recordings concerning the 25A and TP streets is presented.

5.3. Results

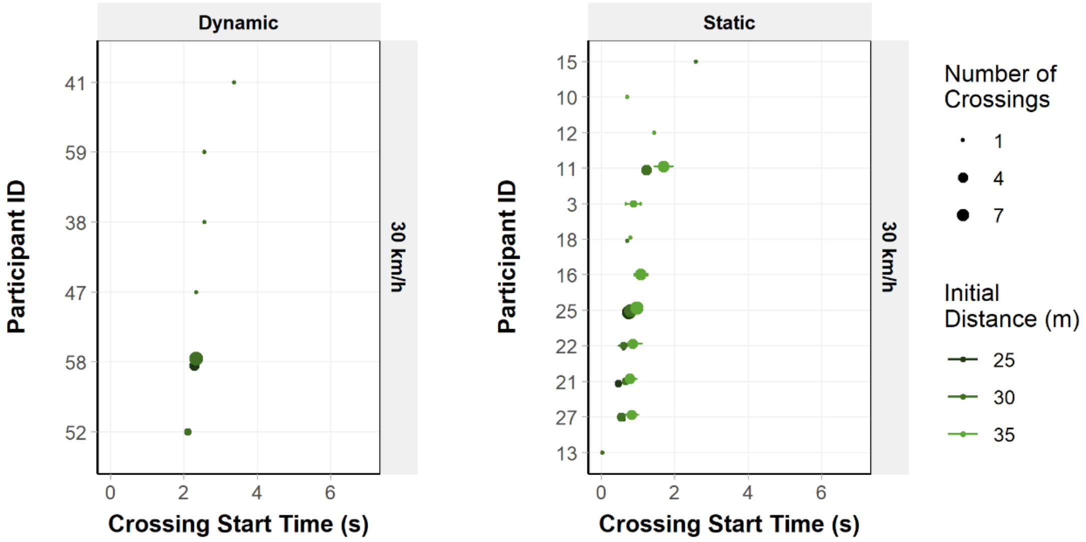
5.3.1 Constant speed pattern

Figure 5.5 and Figure 5.6 show the general distribution of the data by participant and condition (similarly to those of previous chapters, location of the circle along the axis represents the mean response time, the size of the circle represents the number of crossings and the line shows the standard error of the mean; participants are vertically ordered according to mean crossing start time). In general, with few exceptions, the participants took more time to start to cross in the dynamic approach than in static, irrespective of the condition. Table 5.4 and Table 5.5 show the summary of descriptive statistics by condition, in terms of percentage of crossings, percentage of crashes, crossing start time, and TTP, to complement the information presented on the following figures.



(a) (b)

Figure 5.5 – Participants' responses along time of stimulus' presentation, per initial distance, regarding the 20 km/h speed, for Constant speed pattern and for each experimental approach: (a) dynamic; and (b) static.



(a) (b)

Figure 5.6 – Participants' responses as a function of the time of stimulus' presentation, per initial distance, regarding the 30 km/h speed, for Constant speed pattern and for each experimental approach: (a) dynamic; and (b) static.

Table 5.4 – Descriptive statistics of percentage of crossings and crashes for each trial regarding the Constant speed pattern.

			Crossings			**Crashes**
Experimental Approach	**V_i (km/h)**	**$D_{i.mov}$ (m)**	**Mean (%)**	**SD (%)**	**SE (%)**	**Percentage (%)**
Static	20	25	23.00	31.90	5.82	-
		30	41.30	42.30	7.73	-
		35	49.30	40.70	7.43	-
	30	25	4.33	16.80	3.06	-
		30	7.67	17.70	3.24	-
		35	12.70	22.90	4.18	-
Dynamic	20	25	12.30	19.80	3.61	59.50
		30	54.30	39.90	7.28	0.61
		35	74.00	35.00	6.39	0.90
	30	25	0	0	0	0
		30	1.33	7.30	1.33	75.00
		35	5.00	16.80	3.06	20.00

Table 5.5 – Descriptive statistics of crossing start time and TTP for each trial regarding the Constant speed pattern.

			Crossing start time			TTP		
Experimental Approach	**V_i (km/h)**	**$D_{i.mov}$ (m)**	**Mean (s)**	**SD (s)**	**SE (s)**	**Mean (s)**	**SD (s)**	**SE (s)**
Static	20	25	1.07	0.45	0.05	3.62	0.41	0.05
		30	1.18	0.58	0.05	4.53	0.52	0.05
		35	1.31	0.82	0.07	5.22	0.75	0.06
	30	25	0.69	0.19	0.05	2.41	0.23	0.06
		30	0.87	0.49	0.10	2.91	0.43	0.09
		35	1.05	0.50	0.08	3.32	0.43	0.07
Dynamic	20	25	2.74	0.35	0.06	2.08	0.34	0.06
		30	2.83	0.37	0.03	3.16	0.37	0.03
		35	2.93	0.46	0.03	3.81	0.39	0.03
	30	25	-	-	-	-	-	-
		30	2.28	0.15	0.08	1.68	0.21	0.10
		35	2.41	0.30	0.08	2.14	0.25	0.06

5.3.1.1 Percentage of crossings

The percentage of crossings was examined using a three-way repeated-measures ANOVA with intra-subject variables vehicle *initial distance* (3) and *vehicle speed* (2), and the inter-subject variable *experimental approach* (2), as factors (see Figure 5.7). The experimental approach did not significantly influence the participants' percentage of crossings F(1, 58) = 0.07, $\eta^2 = 0.01$, p = 0.79. There was a main effect of vehicle speed, F(1, 58) = 116.21, $\eta^2 = 0.67$, $p < 0.01$, with higher values for the 20 km/h condition compared to the 30 km/h condition. There was also a main effect of vehicle initial distance, F(2, 116) = 90.99, $\eta^2 = 0.61$, $p < 0.01$, with Bonferroni post hoc tests showing that crossing percentages increased significantly with the initial distance ($p < 0.01$).

A significant speed × initial distance interaction was also found, F(2, 116) = 49.74, $\eta^2 = 0.46$, $p < 0.01$. Bonferroni post hoc tests were conducted comparing initial distances within each level of speed. At 20 km/h, there were significant differences between all levels of distance (25 m / 30 m: $p < 0.01$, 25 m / 35 m: $p < 0.01$, 30 m / 35 m: p = 0.01). At 30 km/h significant differences were only found between 25 and 35 m (p = 0.04). The experimental approach × initial speed and experimental approach × initial distance interactions were also significant, $F(1, 58) = 4.79$, $\eta^2 = 0.08$, $p = 0.03$, and $F(2, 116) = 9.21$, $\eta^2 = 0.14$, $p < 0.01$, respectively.

The Bonferroni post hoc tests conducted to compare each level of speed within the experimental approaches revealed significant differences between the percentage of crossings regarding the initial speeds of 20 and 30 km/h in both experimental approaches, static ($p < 0.01$), and dynamic ($p < 0.01$). In turn, in the dynamic approach, there were significant differences between the percentage of crossings regarding all the initial distances (25 m / 30 m: $p < 0.01$, 25 m / 35 m: $p < 0.01$, 30 m / 35 m: $p < 0.01$). The same was verified in the static experiment (25 m / 30 m: $p < 0.01$, 25 m / 35 m: $p < 0.01$, 30 m / 35 m: $p = 0.05$).

The experimental approach × speed × initial distance interaction had also a significant effect on percentage of crossings, $F(2, 116) = 12.79$, $\eta^2 = 0.18$, $p < 0.01$. Bonferroni post hoc tests were conducted comparing experimental approaches within each level of speed with each level of initial distance. Only when the vehicle approached the crosswalk at 20 km/h and from 35 m, the percentage of crossings were significantly higher for the dynamic approach than for the static one ($p < 0.01$).

In both experimental approaches, participants crossed more when vehicle speed was lower, and its initial position was farther from the crosswalk. At 20 km/h, the increase in distance resulted in greater growth of the crossings percentage, being even more evident in the participants' responses that performed the dynamic experiment (see Figure 5.7). However, these percentages do not mean properly safe crossings.

One advantage of the dynamic approach was to allow the exact determination of the occurrence of crashes. Considering the values presented in Table 5.4, it is possible to note that a considerable portion of the crossings made by participants resulted in a crash, particularly when the vehicle approached at 20 km/h from the shorter distance and 30 km/h from 30 m.

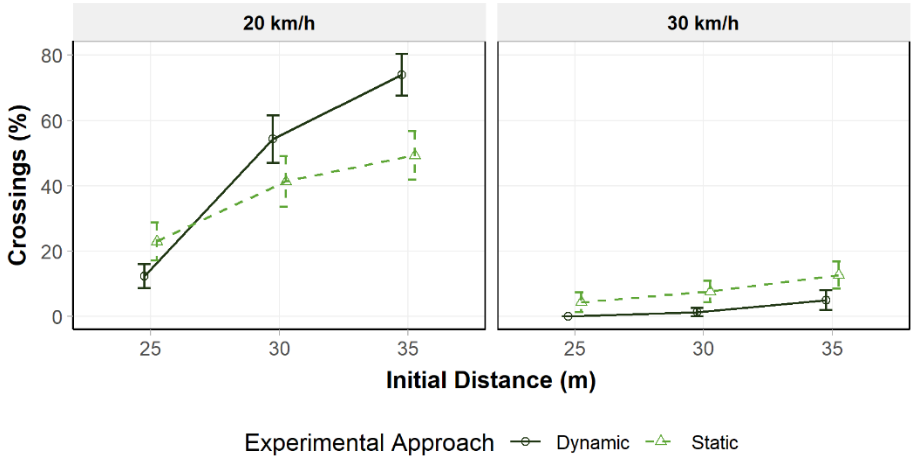


Figure 5.7 – Percentage of crossings and respective mean standard error as a function of experimental approach, per initial distance and initial speed, for Constant speed pattern.

5.3.1.2 Crossing start time

Visual inspection of the residual plots showed deviations from homoscedasticity and skewness of crossing start time distribution, so the model considered to analyse this variable was fitted applying a logarithmic transformation to crossing start time, which corrected the deviations. In this way, an LMM of log(crossing start time) with random effects included for the participant and fixed effects defined for the *initial speed*, *initial distance*, and *experimental approach* was fitted. Satterthwaite's tests showed significant effects of experimental approach, F(1, 53.08) = 46.40, $p < 0.01$, and initial speed, F(1, 790.60) = 3.77, p = 0.05. There was no effect of the initial distance, nor even of any interaction between the considered variables.

In the static approach participants were quicker to start the crossing than in dynamic approach, b = - 0.90, t(58.79) = - 6.57, $p < 0.01$. When the vehicle approached the crosswalk at 30 km/h, participants started to cross sooner, b = - 0.24, t(789.50) = - 2.11, p = 0.04. Considering these results and Figure 5.8 that shows the crossing start time as a function of vehicle initial distance, initial speed, and experimental approach, it is noticeable that the participants' decisions to cross tended to be faster at the highest speed and when they had not walked to perform the crossing task.

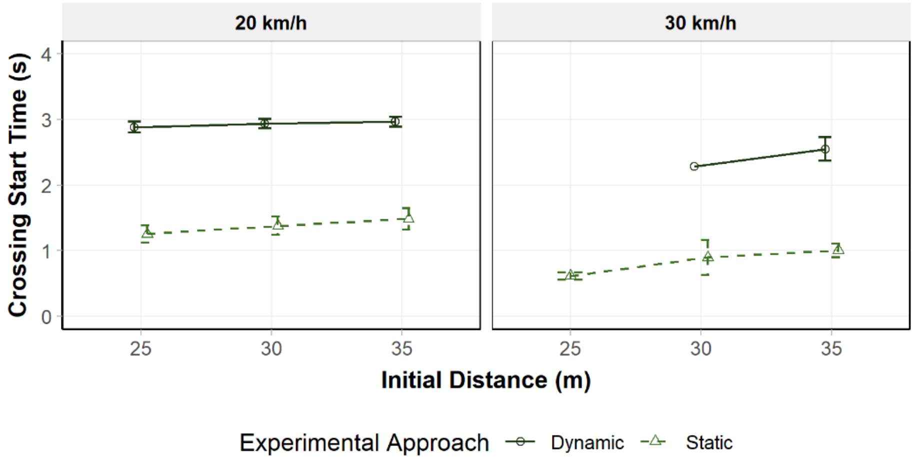


Figure 5.8 – Crossing start time and respective mean standard error as a function of experimental approach, per initial distance and initial speed, for Constant speed pattern.

5.3.1.3 Time-to-passage

The observed TTP appears to vary linearly with the initial TTP, particularly for the results of the static experiment, as already seen in the study presented in Chapter 4 (Figure 4.8), due to the small variations of the crossing start time. The crossing start time analysis done in the previous section showed that for those participants that did cross with the approaching vehicle at 30 km/h, there was an attempt to compensate for the shorter available time. However, this was not enough to compensate for the difference in TTP with the crossing TTP being almost linearly predicted by the Initial TTP. This is clearer for the results of the static experiment than for the dynamic one (Figure 5.9).

Nevertheless, such as presented in Table 5.5, in the dynamic experiment, there were considerable percentages of crashes, particularly for the speed of 20 km/h with which the vehicle started its movement from 25 m far the crosswalk and for the speed of 30 km/h from the initial distance of 30 m. Disregarding the situations where a crash has occurred, it is possible to note, through the analysis of Figure 5.10, that, also in the dynamic approach, the crossing TTP can be almost linearly predicted by the Initial TTP. Furthermore, due to the later crossing start, the participants took riskier decisions in the dynamic approach.

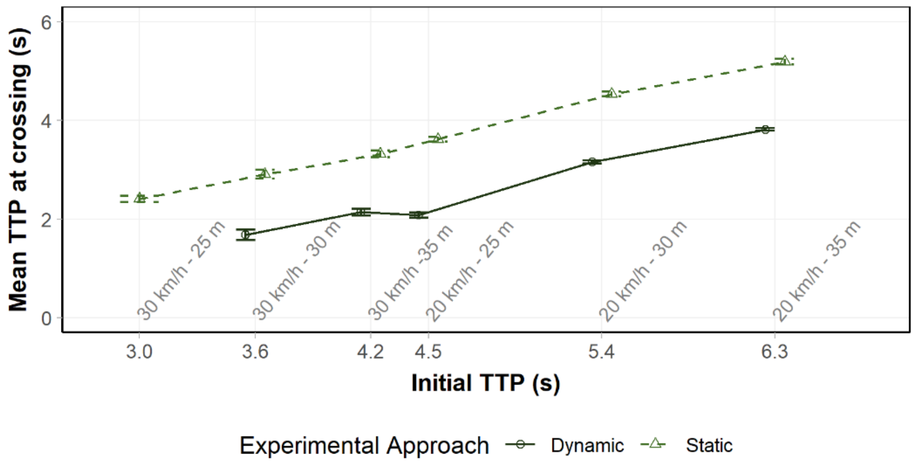


Figure 5.9 – Mean values of TTP at the crossing instant as a function of the TTP at the start of the trial, by experimental approach, for Constant speed pattern.

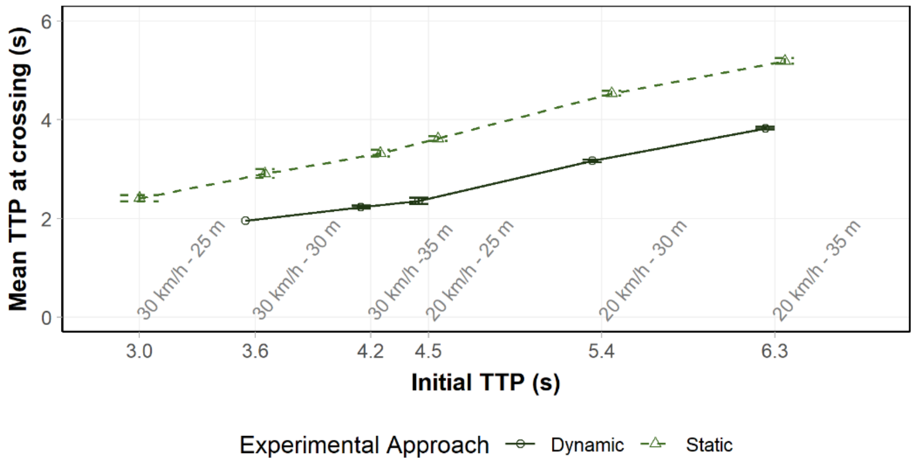
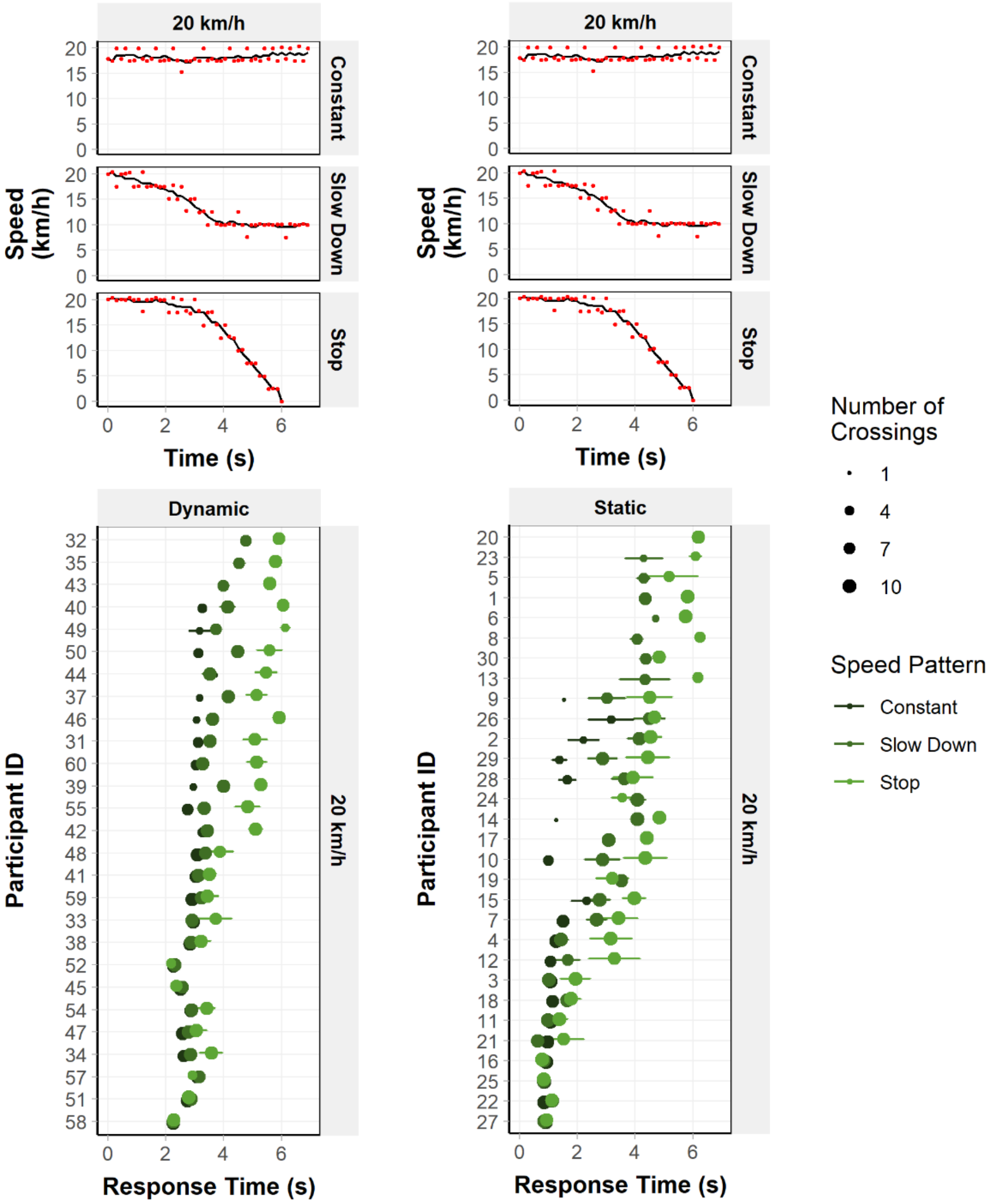


Figure 5.10 – Mean values of TTP at the crossing instant as a function of the TTP at the start of the trial, disregarding crashes, by experimental approach, for Constant speed pattern.

5.3.2 Different speed patterns

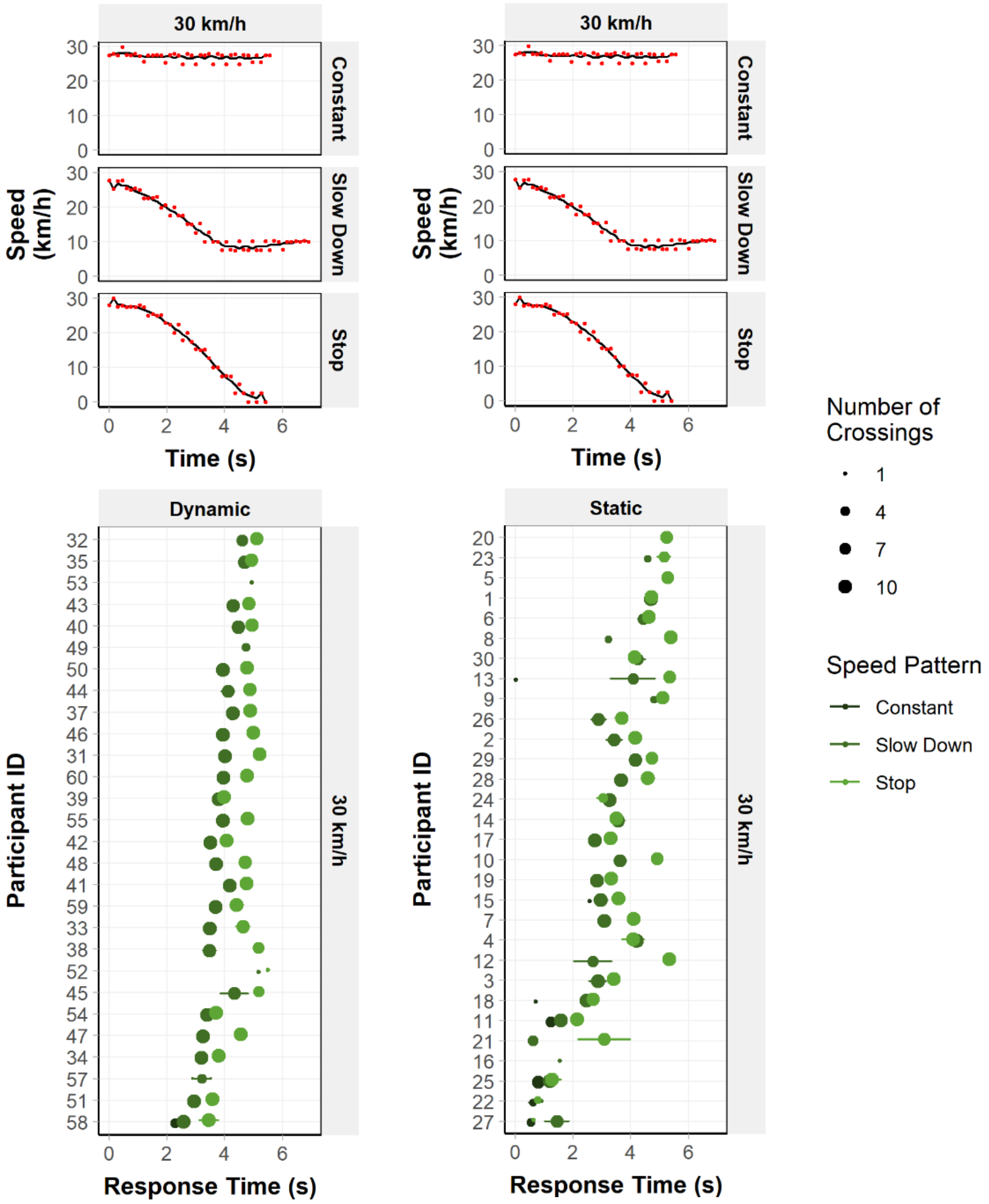
Figure 5.11(a), Figure 5.11(b), Figure 5.12(a) and Figure 5.12(b) show the crossing data for each participant and condition (location of the circle along the axis represents the mean crossing start time, the size of the circle depicts the number of crossings, and the line shows the standard error of the mean) and the speed profile of the vehicle. It is possible to note that the number of crossings increases substantially for the Slow Down and Stop patterns in both experimental approaches, being this particularly clearer in the dynamic approach, in which very few participants had crossed when the vehicle approached them at a constant speed of 30 km/h.

Table 5.6 and Table 5.7 show the summary of descriptive statistics for the condition in terms of percentage of crossings, percentage of crashes, crossing start time, and TTP regarding the different speed patterns.



(a) (b)

Figure 5.11 – Participants’ responses along time of stimulus’ presentation, regarding the initial speed of 20 km/h, per speed pattern and experimental approach: (a) dynamic; and(b) static.



(a) (b)

Figure 5.12 – Participants' responses along time of stimulus' presentation, regarding the initial speed of 30 km/h, per speed pattern and experimental approach: (a) dynamic; and (b) static.

Table 5.6 – Descriptive statistics of percentage of crossings and crashes for all the speed patterns.

Experimental Approach	V_i (km/h)	Speed Pattern	Crossings Mean (%)	Crossings SD (%)	Crossings SE (%)	Crashes Percentage (%)
Static	20	Constant	41.30	42.30	7.73	-
		Slow Down	80.30	27.10	4.95	-
		Stop	87.70	17.90	3.28	-
	30	Constant	7.67	17.70	3.24	-
		Slow Down	69.30	35.80	6.54	-
		Stop	82.70	28.40	5.18	-
Dynamic	20	Constant	54.30	39.90	7.28	0.61
		Slow Down	85.00	30.60	5.59	0
		Stop	79.00	32.70	5.98	0
	30	Constant	1.33	7.30	1.33	75.00
		Slow Down	79.30	34.20	6.25	3.36
		Stop	75.70	38.70	7.07	0

Table 5.7 – Descriptive statistics of crossing start time and TTP for all the speed patterns.

Experimental Approach	V_i (km/h)	Speed Pattern	Crossing start time Mean (s)	Crossing start time SD (s)	Crossing start time SE (s)	TTP Mean (s)	TTP SD (s)	TTP SE (s)
Static	20	Constant	1.18	0.58	0.05	4.53	0.52	0.05
		Slow Down	2.63	1.63	0.11	4.12	0.58	0.04
		Stop	3.64	2.19	0.14	4.68	6.07	0.37
	30	Constant	0.87	0.49	0.10	2.91	0.43	0.09
		Slow Down	3.10	1.24	0.09	3.06	0.33	0.02
		Stop	4.01	1.30	0.08	6.83	10.50	0.67
Dynamic	20	Constant	2.83	0.37	0.03	3.16	0.37	0.03
		Slow Down	3.36	0.79	0.05	3.80	0.35	0.02
		Stop	4.34	1.51	0.10	3.86	4.96	0.32
	30	Constant	2.28	0.15	0.08	1.68	0.21	0.10
		Slow Down	3.81	0.71	0.05	3.08	0.34	0.02
		Stop	4.56	0.67	0.04	7.34	11.50	0.77

5.3.2.1 Percentage of crossings

The percentage of crossings was also examined here through a three-way repeated-measures ANOVA. The *vehicle speed pattern*, the *initial speed*, and the *experimental approach* were the considered factors. Main effects were found for initial speed, F(1, 58) = 41.82, $\eta^2 = 0.42$, $p < 0.01$, and speed pattern, F(2, 116) = 146.18, $\eta^2 = 0.72$, $p < 0.01$, but not for the experimental approach F(1,58) = 0.03, $\eta^2 < 0.01$, $p = 0.87$. A significant effect of the initial speed × speed pattern interaction was also found, F(2,116) = 49.33, $\eta^2 = 0.46$, $p < 0.01$.

Bonferroni post hoc tests were conducted comparing the different speed patterns and the initial speed within speed profiles. Generally, there was a significant increase in the percentage of crossings from Constant to Slow Down ($p < 0.01$) and from Constant to Stop ($p < 0.01$), but not from Slow Down to Stop ($p = 1.00$). Contrasts within each speed pattern show differences between 20 km/h and 30 km/h for the Constant speed ($p < 0.01$), and for the Slow Down ($p = 0.03$), but not for the Stop ($p = 0.28$).

The experimental approach × speed pattern × initial speed interaction had also a significant effect on percentage of crossings, F(2,116) = 4.72, $\eta^2 = 0.08$, $p = 0.01$. Bonferroni post hoc tests conducted to compare the initial speed within the experimental approaches with each speed pattern showed that only in the dynamic approach and in Constant speed pattern ($p < 0.01$), and in static approach in Constant ($p < 0.01$) and Slow Down patterns ($p = 0.04$) there were significant differences in the percentage of crossings compared between both initial speeds.

The results show that the participants crossed significantly more when the vehicle slowed down or stopped (see Figure 5.13). They also show that the participants crossed more when the vehicle was approaching at 20 km/h than at 30 km/h. Still, this difference was only significant when the vehicle approached at a constant speed or slowed down. Figure 5.13 shows that, in the last one, the differences revealed by the Bonferroni post hoc test are not clear. In turn, the experimental approach could not cause any difference in the participants' crossing decision when comparing the different vehicle speed patterns of approach to the crosswalk.

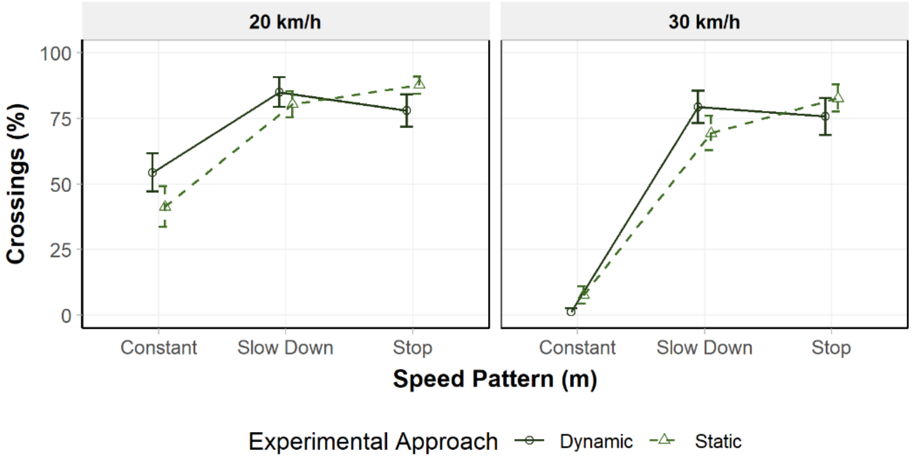


Figure 5.13 – Percentage of crossings and respective mean standard error as a function of experimental approach, per initial speed and speed pattern.

5.3.2.2 Crossing start time

An LMM of crossing start time with random effects included for the *participant* and fixed effects defined for the *initial speed*, *speed pattern*, and *experimental approach* was fitted. Visual inspection of the residual plots showed no deviations from homoscedasticity or skewness. Satterthwaite's tests showed significant effects of vehicle initial speed, F(1, 2167.54) = 9.73, $p < 0.01$, speed pattern, F(2, 2168.20) = 187.69, $p < 0.01$, experimental approach, F(1, 66.85) = 6.71, p = 0.01, and an interaction between initial speed and speed pattern, F(1,2165.70) = 3.42, p = 0.03. None of the interactions of the experimental approach with the other variables were significant.

The model was refitted, discarding the experimental approach's interaction with the other variables, and contrasts were used to compare the different initial speeds, the speed patterns, the interaction between both, and the experimental approaches. Although the results of Satterthwaite's tests have revealed that initial speed explains the participants' crossing start time, contrasts revealed that the crossing start time was not significantly different when comparing the initial speed of 30 km/h to the 20 km/h, b = 0.21, t(2172.19) = 1.08, p = 0.28.

Regarding the speed patterns, differences were found between Constant and Slow Down patterns, b = 0.43, t(2172.08) = 6.12, $p < 0.01$, and between Constant and Stop, b = 1.32, t(2173.78) = 18.84, $p < 0.01$, indicating a significant increase in crossing start time from Constant to Slow Down and also from Constant to Stop. A third contrast was used to compare the experimental approach, showing that participants were significantly quicker to take their decision in static experiment participants than those who have performed the dynamic experiment, b = - 0.64, t(55.45) = - 2.40, p = 0.02. The last contrast done to assess the differences between the initial speeds of 20 km/h and 30 km/h within the speed pattern revealed no significant differences in crossing start time caused by the interactions between all the levels of initial speed and speed pattern variables.

Figure 5.14 shows that the crossing start time distribution is very similar between the different initial speeds, except the point corresponding to the dynamic approach's Constant speed pattern. An apparent increase in the time participants spend from the Constant speed pattern to the Slow Down, and the Stop is also shown. Considering the results of the analysis of the percentage of crossing and the response time, it is observed that, such as in the static experiment, in the dynamic experiment, the participants felt to have more time to cross the road safely when the vehicle speed varied, having waited until the vehicle slowed down and crossed.

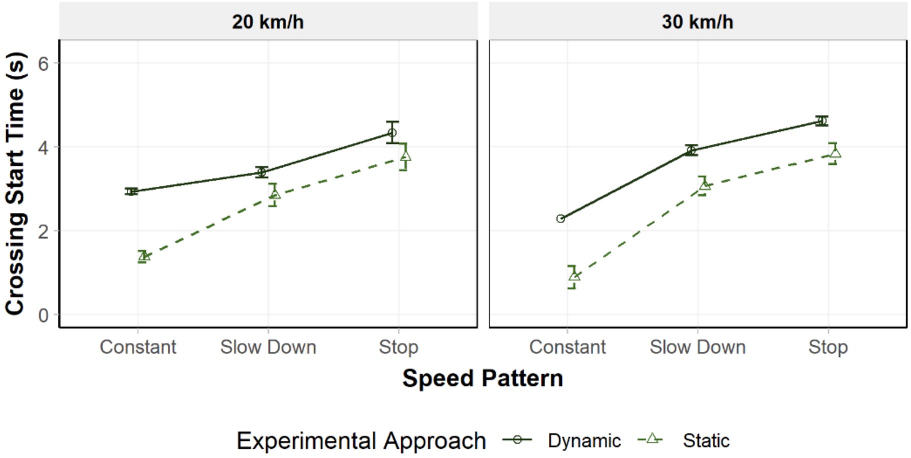


Figure 5.14 – Crossing start time and respective mean standard error as a function of experimental approach, per initial speed and speed pattern.

However, the most notorious difference seen in Figure 5.14, also evidenced by Figure 5.8, is between the experimental approaches. In the dynamic approach, participants have spent, on average, about 0,8 s more to take their crossing decision than those who performed the static experiment. This difference was already expected. In the static experiment, the participants were placed at the same point on the curb during the entire experiment, from the start till the end of each stimulus. In contrast, in the dynamic experiment, the participants had to walk 3 m, after the stimulus had started, until they reached the curb and cross.

5.3.2.3 Time-to-passage

An LMM of TTP with subject ID as random effect and *vehicle initial speed*, *speed pattern* and *experimental approach* as fixed factors was also fitted. Satterthwaite's tests showed significant effects of speed pattern, F(2, 2179.55) = 27.98, $p < 0.01$, and an interaction effect between initial speed and speed pattern, F(2, 2168.94) = 25.93, $p < 0.01$. There was no significant effect of the initial speed, F(1, 2178.94) = 0.39, $p = 0.53$, nor of the experimental approach, F(1, 99.46) = 0.93, $p = 0.34$.

The model was refitted, discarding the experimental approach factor, and contrasts were used to compare the different speed patterns. A first one compared the Constant and Slow Down speed patterns, and non-significant differences were found between them. A second contrast compared the Constant and Stop patterns, and it also showed a non-significant difference between them. A third contrast compared the Constant and Slow Down patterns for each one of the different initial speeds, revealing once again a non-significant difference between them. Lastly, a fourth contrast showed significant differences between the Constant and Stop patterns within each one of the different initial speeds, $b = 3.68$, t(2183.91) = 3.16, $p < 0.01$, showing that the TTP was particularly longer for the Stop when the initial speed of the vehicle was 30 km/h (see Figure 5.15).

The TTP for the Slow Down pattern is similar to the ones for the Constant. Nevertheless, as shown in Chapter 4, the percentage of crossings was notoriously higher, indicating that participants have made a substantially different risk assessment, believing that the vehicle would stop. The large increase in TTP for the 30 km/h also helps to explain that, showing that, in both experimental approaches, the participants waited for the vehicle to almost stop before starting to cross.

No significant differences were found between experimental approaches. However, Figure 5.15 shows, particularly for the Stop pattern and the initial speed of 30 km/h, that the participants who performed the dynamic experiment have accepted higher TTPs. The opposite can be said regarding the stimuli corresponding to the Constant speed pattern, considering both initial speeds.

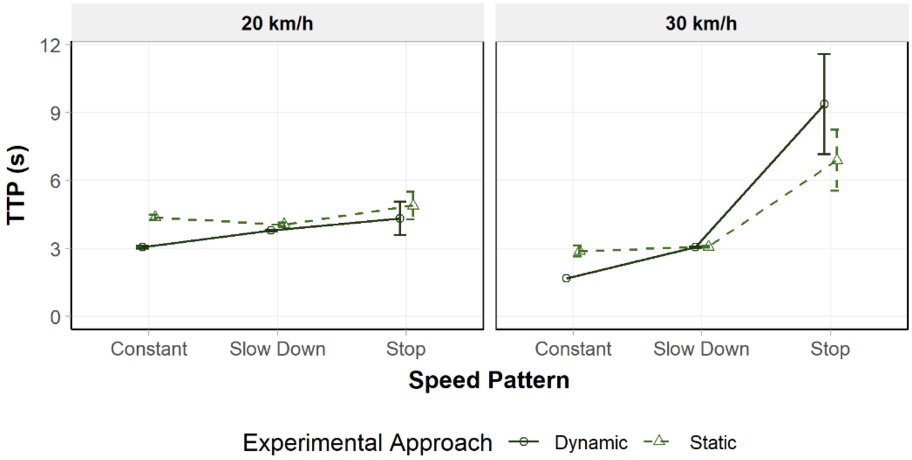


Figure 5.15 – TTP and respective mean standard error as a function of experimental approach, per initial speed and speed pattern.

5.3.3 Comparison between virtual and real environments

An LMM of TTP with subject ID as a random effect and the *speed pattern* and the *data gathering approach* as fixed factors were fitted to compare the results obtained with each experimental approach's performance and video recordings. Satterthwaite's tests just showed significant speed pattern effects, F(2, 994.40) = 5.15, $p < 0.01$. There was no significant effect of the data gathering approach, F(2, 106.69) = 0.82, $p = 0.44$, nor of the data gathering approach × speed pattern interaction, F(4, 1432.49) = 1.90, $p = 0.11$.

The model was refitted, removing the experimental approach factor, and contrasts were used to compare the different speed patterns. A first contrast compared the Constant and Slow Down speed patterns and, such as in the previous section, non-significant differences were found between them. A second contrast compared the Constant and Stop patterns and it showed a significant difference between them, b = 1.35, t(2769.94) = 5.47, $p < 0.01$. A third contrast has compared the Slow Down and Stop patterns and also revealed a significant difference between them, b = 1.74, t(2747.00) = 7.72, $p < 0.01$. These results meet those ones presented in section 5.3.2.3, demonstrating that the TTP was in general longer, not only in virtual environment experiments but also in real crossing situations, for the Stop pattern.

Furthermore, the statistical analysis also revealed that the different data collection methods did not induce substantial differences in how pedestrians estimate the time they need to cross the road safely. Figure 5.16 shows the referred similarities between the three methods. Although the results of the LMM do not show it, a slight difference can be noticed when comparing the static approach with the other two, particularly in the TTP observed in the Constant Speed pattern condition.

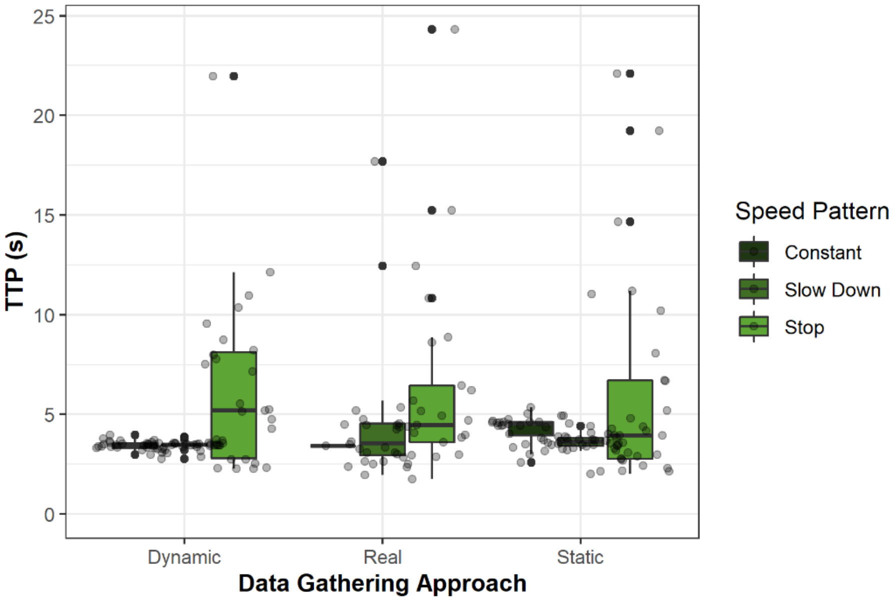


Figure 5.16 – Comparison of the TTP obtained in real and virtual environment through the execution of each experimental approach, per speed pattern.

5.4. Discussion

As referred in the introductory section of this chapter, according to Feldstein *et al.* (2016), the capacity of making participants feel they are actually present in the virtual environment determines the realism of the environment and the usability of the simulator. This will depend on the quality of the graphical representation, sound, and interaction possibilities. This study compares the results of the experimental approach used in Chapter 4, where participants had their movements entirely restricted, with the ones obtained through an experimental approach that allowed them to walk along a crosswalk, aiming to assess the impact of the interaction between the participant and virtual environment on crossing decision-making.

Regarding of the crossing decisions observed when the vehicle approached the participants at a constant speed, and congruently with the results obtained in Chapter 4, the vehicle speed and initial distance were the most determining variables for the participants' crossing decisions. The percentage of crossings only differed between the two experimental approaches when the vehicle approached at 20 km/h from the initial distance of 35 m, *i.e.*, in the most favourable condition to cross and in which the percentage of crossings was higher. Such as in the static experimental approach, in the dynamic method, crossing percentages increased with vehicle initial distance and decreased with its speed. These results confirm again the important role of vehicle speed in crossing decisions when balanced with the distance weight, contrasting with Feldstein and Dyszak (2020) results.

Crossing start times were not affected by the initial distance. However, the vehicle speed and the experimental approach had a significant impact on participants' time to decide to cross. In both experimental approaches, higher speeds have prompted faster decisions. As for the experimental approach's effect, it can be easily explained by the distance of 3 m that participants had to walk after the beginning of the stimuli presentation and before reaching the curb in the dynamic experiment. Except for the condition characterized by the speed of 30 km/h and the initial distance of 25 m, where none crossing in the dynamic approach, the crossing start times assume the same trend in both experimental methods. In the dynamic approach, the crossing start times were, on average, 1.58 s higher than in the static experiment. For this reason, and for both experimental approaches, it is possible to affirm that shorter stimuli led to less time to take the decision, agreeing with Lobjois and Cavallo (2009).

Again, the higher speeds and close distances have prompted a similar sense of urgency, accelerating the decision processes. This had a repercussion on the accuracy of judgements. In the dynamic experiment, where it was possible to determine the number of crashes, considering the values presented in Table 5.4, they expressively occurred when vehicle speed was the highest and when the vehicle approached the crosswalk at 20 km/h from the shortest distance. Thus, it was possible to note, with both experimental approaches, that the TTP and the crossing start time were directly related when the vehicle approached at a constant speed.

Regarding the analysis of the stimuli considering the three different types of speed pattern, the results showed that the initial speed of the vehicle had a significant influence both on the percentage of crossings, with the participants crossing more often when the initial speed of the vehicle was 20 km/h, and on the crossing start time. This is valid particularly for the dynamic experiment, since in Chapter 4, through the execution of the static experiment, it was verified that crossing start time (response time) was significantly longer when the vehicle approached the crosswalk at an initial speed of 30 km/h.

In general, participants crossed more when the vehicle varied its speed (Slow Down and Stop patterns). In these patterns, most of the static experiment participants and all the participants of the dynamic experiment waited for a speed considerably lower than the initial speed to cross the virtual road. The crossing start time was longer in the dynamic compared to the static experiment. However, as in the constant speed pattern, the delay in crossing decision-making verified in the dynamic experiment is defined by the distance the participants had to walk before arriving at the crosswalk and not by a better ponderation made before the crossing, as indicated by similarity between the percentage of crossings for both experimental approaches.

The TTP analysis showed that, for both experimental approaches only the condition characterized by the Stop Pattern with an initial speed of 30 km/h was significantly different from the others. For this condition, the participants crossed mostly when the vehicle speed was almost 0 km/h, making the TTP higher than in the other conditions. The TTP values for the different speed patterns analysis confirm the existing similarity between both experimental approaches.

Considering the general comparison between the results of the static and dynamic experiments with those obtained through the analysis of the two videos recorded in the real environment, it was possible to note that there was no significant difference between them. Thus, and considering all the advantages of carrying out experiments in virtual environments, (Deb *et al.*, 2017), this study confirms that the use of a simulator, regardless of the practical experimental approach, is a sustainable option to take in the pedestrian safety research area.

On the other hand, the choice of the approach to be implemented in each study must depend on the desired amount of information to get. With the possibility of extracting participants' trajectories and speeds, the dynamic approach allows calculating the most various surrogate safety indicators (*e.g.*, PET, TTC_{min}, TA, etc. (Johnsson *et al.*, 2018a)), contrary to the static approach. Besides, it allows to perform the crossing task in a similar way to that occurring in the real world. However, an experience where the participants walk along a crosswalk is technically more demanding than the one where they click on a button when they decide to cross, because in terms of development effort, it is more complex to model and implement the sound and the visual scenarios. All these characteristics must be well pondered in the design phase of each study. The static experience can be more effective when applied in studies where a great detail of information is unnecessary, while the dynamic experience can be useful for more in-depth studies.

5.5. Conclusions

Such as the sound, the possibility of letting participants move freely turns the simulator more realistic and immersive, allowing them to have a more complete interaction with the virtual world. In this way, this work aimed to assess the implementation of a more realistic approach for studying pedestrian crossing behaviour, comparing two different experimental approaches: (i) the static approach used in the studies presented in Chapter 3 and Chapter 4, in which the participants were required to decide when they would cross the road by clicking on a button, standing in the same position during all the experiment; (ii) the dynamic approach, in which the participants were instructed to cross the virtual road, walking along a semi-virtual crosswalk.

The overall analysis reveals that the experimental approach was not a determinant factor on the participants' crossing decision task. As in Chapter 3 and Chapter 4, the obtained results support the general conclusion that the vehicle speed and initial distance, as well speed profile, were the variables used by participants to make their decision.

The static approach has the advantage of turning the experimental task simpler and less time consuming, with instructions easily assimilated and performed by the participants. The dynamic is more time-consuming due to the circuit that pedestrians must walk to answer each of the stimuli presented. However, it is more naturalistic than the static experiment. It allows gathering a greater quantity of information, such as participants' speed and position and the determination of crash occurrence. Regardless of these main characteristics, both experimental approaches revealed to be valid for studying the pedestrians' crossing decision-making. The use of each of the approaches in future studies must be considered depending on the desired type of information and the detail intended.

6. ANALYSIS OF PEDESTRIAN BEHAVIOUR IN VIRTUAL ENVIRONMENT

6.1. Introduction

Several studies addressing the pedestrians' behaviour when crossing the road have been carried out to identify factors that can affect and influence it, as showed in Chapter 1 and Chapter 2. Identifying factors that lead to risky behaviour is a way to facilitate and increase the effectiveness of public policies aimed to solve the big problem that is the high accident rate and, consequently, pedestrian mortality on the roads.

As simulators become more available to researchers, some studies have been carried out using virtual environments as a tool to collect data, which enables a finer analysis of participants' behaviour and decision-making (*e.g.* (Cavallo *et al.*, 2019; Charron *et al.*, 2012; Deb *et al.*, 2018b; Feldstein *et al.*, 2016; Meir *et al.*, 2015; Morrongiello *et al.*, 2015; Schwebel *et al.*, 2008; Simpson *et al.*, 2003; Sween *et al.*, 2017; Thomson *et al.*, 2005; Zito *et al.*, 2015)). This has been the main method of study reported in Chapters 3, 4, and 5 of this document.

Simulators allow a greater control over the variables considered in a study, in addition to allowing crossings without jeopardizing the safety and physical integrity of the participants (Cavallo *et al.*, 2019; Charron *et al.*, 2012; Deb *et al.*, 2017; Dommes and Cavallo, 2011; Schwebel *et al.*, 2012; Simpson *et al.*, 2003). This makes them a very interesting and appealing tool to use in studies concerning the identification of impacting factors related to road infrastructure and the built environment in pedestrian crossing decision-making. Factors identified in the literature, such as the road width, the number of lanes, the width and quality of the sidewalks, the parking spaces, among other physical characteristics of the simulated streets, can be easily manipulated from the point of view of their dimensions. Different variations can be integrated into the virtual scenarios to be presented in each experiment.

This part of the study, which comes as a sequence of all the work carried out and presented in the previous chapters, takes advantage of the simulator developed throughout the ANPEB project, within which this doctoral project was developed, to complement the results obtained in the analysis of pedestrian behaviour in the real environments (Chapter 2), through the application of the experimental protocol developed and tested with the execution of the experiments described on Chapter 5. However, in this case, four new virtual scenarios were added to the two implemented in the study presented on the previous chapter, aiming to assess the influence of a set of factors related to the characteristics of the road and pedestrian infrastructure, without disregarding the participants' age and sex, as well as the speed of approach of the vehicle, in the participants' crossing decision-making, through the construction of two models: one for TTP and other fot TTC_{min}.

6.2. Materials and Methods

6.2.1 Participants

A sample of 45 adults were recruited from the University of Minho community, in Portugal. One third of them were part of the sample of participants that performed the dynamic experiment presented in Chapter 5. The participants were divided into three distinct groups. To each group was associated a different pair of virtual scenarios where they performed the experiment. The details about the demographic characteristics of the participants are presented in Table 6.1.

Table 6.1 – Participants' demographic characteristics.

	Group			
	I	**II**	**III**	**Total**
Age	23 - 39 years (m = 30.00; sd = 4.95)	21 - 38 years (m = 29.00; sd = 5.45)	21 - 39 years (m = 27.40; sd = 6.08)	21 - 39 years (m = 28.80; sd = 5.62)
Sex	53 % Male; 47 % Female	53 % Male; 47 % Female	47 % Male; 53 % Female	51 % Male; 49 % Female

Also, in this study, before the experiment, all participants answered a questionnaire regarding their hearing, visual, and mobility conditions. None of them reported any impairing condition. All participants gave their written informed consent. The experiments were conducted in accordance with the principles stated in the 1964 Declaration of Helsinki.

6.2.2 Virtual environment

Three combinations of 15 participants and two scenarios were used in this study. By scenarios one means a particular virtual street (replicated from one of the real streets analysed in chapter 2). Each individual combination was presented to one of the three groups:

- Group I: the scenarios of the 25A and TP streets used in the studies in the virtual environments previously presented (Chapter 3, Chapter 0 and Chapter 5) (see Figure 6.1(a) and Figure 6.1(b));
- Group II: the scenarios of the BMJ and SG streets (see Figure 6.1(c) and Figure 6.1(d));
- Group III: the scenarios of CL and AGC streets (see Figure 6.1(e) and Figure 6.1(f)).

The scenarios' modelling was done considering the real characteristics and dimensions of each street (Table 6.2).

Table 6.2 – Main characteristics of each one of the six scenarios.

	Street					
	25A	**TP**	**BMJ**	**SG**	**CL**	**AGC**
Length of the crosswalk (m)	7.85	7.13	9.96	12.5	8.97	7.03
Average width of the lanes (m)	2.87	3.57	3.26	3.00	3.32	2.56
Width of the street to park (m)	4.23	10.12	1.92	5.17	2.34	7.15
Average width of the sidewalks (m)	4.17	4.11	1.52	2.96	1.32	1.95
Width of the crosswalk (m)	3.40	5.12	3.04	5.35	3.00	3.54
Number of lanes	2	2	2	4	2	2

The textures used to model the scenarios were obtained through photos and edited using Adobe® Photoshop CC 2015 before being included in the 3D model. The physical dimensions of the virtual elements were equalized to the real-world measurements.

The method to model a vehicle's movement was the same used in the studies in the virtual environments presented in the two previous chapters. Once again, it is important to mention that speeds above 30 km were not considered since this study aimed to evaluate the pedestrians' crossing decision-making, considering the approaching of a vehicle at short distances from the crosswalk in different scenarios. As previously referred, it was assumed that higher speeds would lead to the absence of useful data because participants would rarely cross.

(a) (b)

(c) (d)

(e) (f)

Figure 6.1 – The six scenarios considered in this study: (a) 25A; (b) TP; (c) BMJ; (d) SG; (e) CL; (f) AGC.

6.2.3 Stimuli

The same visual and auditory stimuli were presented to the three groups of participants. Only the visual scenarios changed. The ten conditions shown in Table 4.2 were repeated five times for every participant. Throughout the experiment, 100 stimuli were presented in a random order (10 movement conditions × 5 repetitions × 2 streets) to each participant. The virtual model of the approaching vehicle used in the experiment was the same used in the experimental task performed in the study of Chapter 5 (see Figure 5.1).

The auditory component of the stimuli was composed of the same auralized CPX sounds used in the experiments presented in Chapter 5 (see section 5.2.2.).

6.2.4 Instruments

The experiment was conducted in the same room and using the same CAVE type system used in the studies described in the three previous chapters (see section 3.2.4).

6.2.5 Experimental procedure

The experimental procedure adopted in this study concerns the same used in the dynamic approach described in section 5.2.5 of Chapter 5. Equipped with the headset and the 3D glasses, participants were instructed to walk along the predefined circuit shown in Figure 5.3 and cross the virtual crosswalk when they felt safe to do so. As in the other experiments, participants completed an experimental session made of two main blocks, each one using one of the two respective scenarios, preceded by a training block composed of 4 stimuli. There was a gap of 5 minutes or more between the two main blocks to rest, depending on the participant's wishes.

6.2.6 Analysis

The street scenario's influence on the participants' crossing decision-making was analysed in terms of the percentage of crossings, percentage of crashes, crossing start time, TTP, and TTC_{min}. As in Chapter 5, the percentage of crossings was calculated, for each participant, by assuming that the participant had crossed the half-length of the crosswalk before the vehicle stopped or passed in front of them.

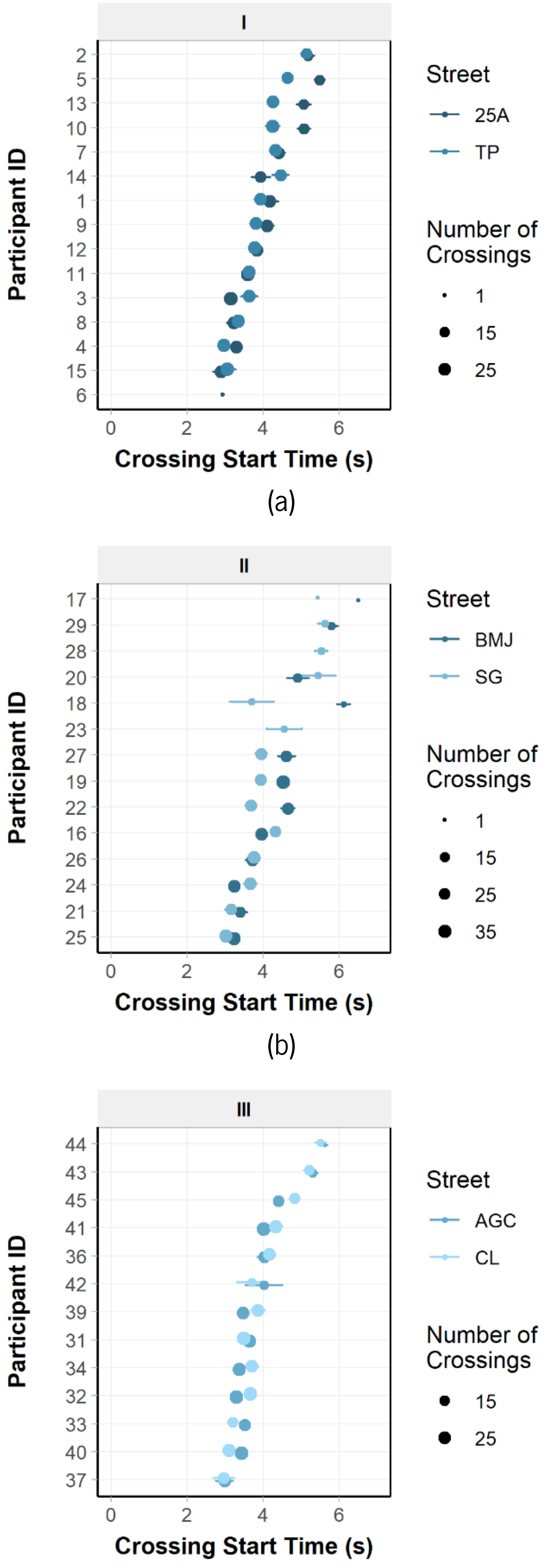
The percentage of crashes corresponds to the percentage of crossings which resulted in virtual crashes. The crossing start time corresponds to the time from the beginning of the stimulus presentation until the moment when the participant took the first step on the crosswalk. The definitions of TTC_{min} and TTP are presented in section 2.2.3 (see Expressions 2.1 and 2.2). The influence of the street scenario and vehicle's movement condition variables on the two mentioned surrogate safety indicators was assessed using mixed-effects regression models with random effects included for the participant and fixed effects defined for the two variables mentioned above. The use of LMMs is justified by the existence of missing values in the data, corresponding to trials in which participants did not cross, and by the experimental design, in which three groups of participants performed the experiment in three different pairs of street scenarios.

Lastly, two models explaining TTP and TTC_{min} were constructed to assess the influence of several variables concerning the participants' demographic characteristics, the characteristics of the road and pedestrian infrastructure, and the vehicle's approaching speed on the participants' crossing decision, as well on the severity of pedestrian-vehicle encounters. This approach followed the one described in Chapter 2 (section 2.2.3), where LMM technique was also used. However, when the data variation justifies, linear regression models were applied.

6.3. Results

6.3.1 Crossing decision

Figure 6.2 shows the general distribution of the data by participant and scenario (location of the circle along the axis represents the mean response time, the size of the circle depicts the number of crossings, and the line shows the standard error of the mean; participants are also here vertically ordered according to mean response time). Table 6.3 summarizes the descriptive statistics for the condition in terms of percentage of crossings, crossing start time, and percentage of crashes to complement the information presented on the following figures regarding the analysis of data in terms of the referred variables.



(a)

(b)

(c)

Figure 6.2 – Participants' responses along time of stimulus' presentation, per group of participants and respective street scenarios: (a) Group I; (b) Group II; and (c) Group III.

Table 6.3 – Descriptive statistics of percentage of crossings, crossing start time and crashes registered by group of participants and respective street scenarios.

		Crossings			**Crossing start time**			**Crashes**
Group	**Street**	**Mean (%)**	**SD (%)**	**SE (%)**	**Mean (s)**	**SD (s)**	**SE (s)**	**Percentage (%)**
I	25A	44.10	44.90	3.67	3.93	1.13	0.06	3.32
	TP	50.30	47.40	3.87	3.87	1.02	0.05	1.59
II	BMJ	36.90	46.70	3.95	4.05	1.07	0.07	12.00
	SG	35.10	42.80	3.50	3.83	0.99	0.06	8.75
III	AGC	39.20	44.60	3.64	3.69	0.92	0.05	4.42
	CL	41.60	44.90	3.79	3.84	1.05	0.06	4.47

An LMM of the percentage of crossings with random effects included for the *participant*, and fixed effects established for the *vehicle's movement condition* (see Table 4.2) and the *street scenario* was fitted. Meeting the results obtained in the three previous chapters, Satterthwaite's tests showed significant effects of the vehicle's movement condition, F(9, 777.73) = 167.65, $p < 0.01$. The street scenario, F(5, 98.41) = 1.41, p = 0.23, and the street scenario × condition interaction, F(45, 777.73) = 1.13, p = 0.26, were non-significant to the percentage of crossings. Analysing Figure 6.3 and Table 6.3, it is possible to note that the percentage of crossings is very similar between the street scenarios within the same group and not much different between groups.

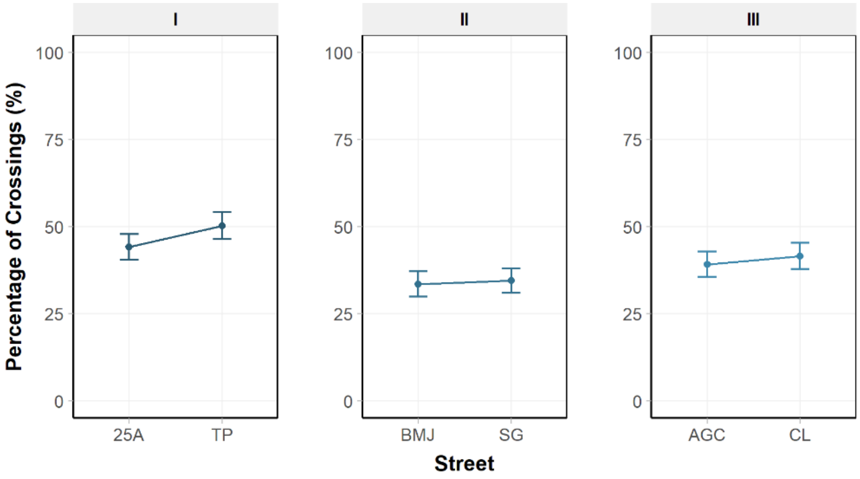


Figure 6.3 – Percentage of crossings and respective mean standard error as a function of street scenario, per group of participants.

Since this study aims to assess the influence of the street and their characteristics on participants' crossing decision-making, and due to the exhaustive exploration of the influence of the vehicle's approaching movement previously carried out, the analysis of the influence the vehicle's movement condition is not deepened in this chapter.

Regarding the percentage of crashes, an LMM was constructed considering random effects for the *participant* and fixed effects for the *vehicle's movement* and the *street scenario*. Such in the analysis of the percentage of crossings, Satterthwaite's tests showed only significant effects of the vehicle's movement condition, F(9, 778.04) = 10.60, $p < 0.01$. The street scenario, F(5, 128.41) = 2.12, p = 0.23, and the street scenario × condition interaction, F(45, 778.04) = 0.95, p = 0.58, had non-significant effect on percentage of crashes.

Analysing Figure 6.4 and Table 6.3, the number of crashes is expressly higher in the scenarios used by group II than the other groups. However, this difference exists because of Participant 17, who crossed only two times in 100 trials (see Figure 6.2), and in both, he/she was virtually hit by the vehicle. In this way, the percentage of crashes regarding group II was inflated by the percentage of crashes regarding the mentioned participant (100 %).

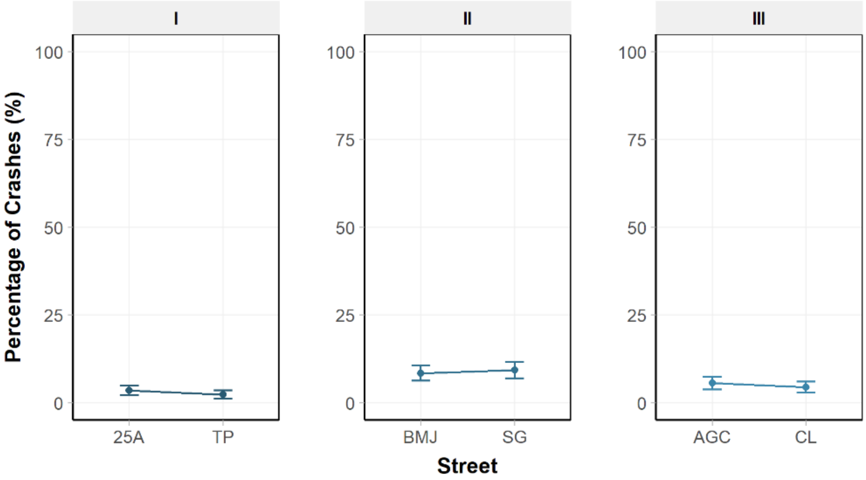


Figure 6.4 – Percentage of cashes and respective mean standard error as a function of street scenario, per group of participants.

Visual inspection of the residual plots showed deviations from homoscedasticity and skewness of crossing start time distribution, so the model considered for analysis of this variable was fitted applying a logarithmic transformation to the crossing start time, which corrected the deviations. An LMM of log(crossing start time) with random effects included for the *participant* and fixed effects defined for the *street scenario* and *vehicle's movement condition* was fitted. Satterthwaite's tests showed significant effects of vehicle's movement condition, F(8, 1727.72) = 163.58, $p < 0.01$. There was no effect of the street scenario, F(5, 116.12) = 1.38, p = 0.24, nor of the scenario × condition interaction, F(36, 1726.91) = 0.99, p = 0.48. Figure 6.5 shows the similarity between the crossing start time registered for every group of participants and respective road scenarios.

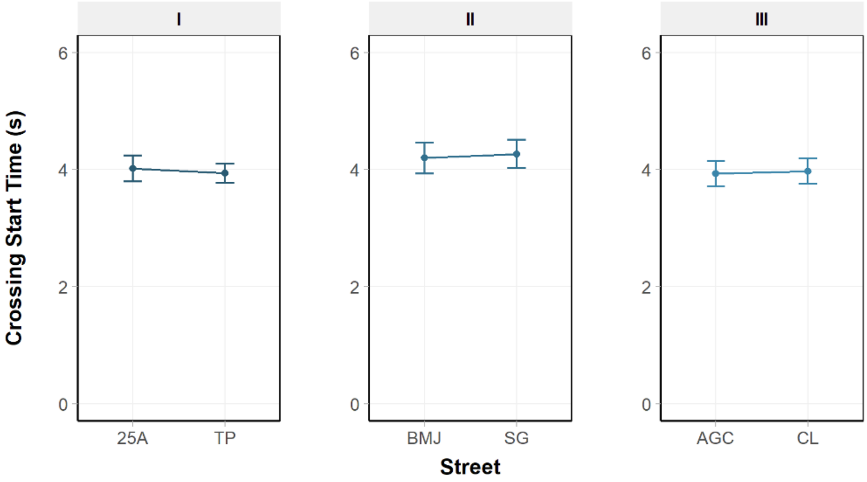


Figure 6.5 – Crossing start time and respective mean standard error as a function of street scenario, per group of participants.

6.3.2 Time-to-passage

As a first step, due to deviations from homoscedasticity and skewness of TTP distribution, an LMM of log(TTP) was constructed, considering random effects for the *participant* and fixed effects for the *vehicle's movement condition* and the *street scenario*. However, the analysis of the residual plots showed that, even with the TTP log transformation, those deviations were still existing due to outliers with very high TTP values on the dataset (see Figure 6.6). These values are concerned to a few situations in which participants started to cross when the vehicle was almost stopped.

To deal with the referred deviations, the TTP outliers were removed respecting Expression 6.1, and the LMM of log(TTP) was reconstructed with the same formulation.

$$Q_1 - 1.5 \times IQ \leq TTP \leq Q_3 + 1.5 \times IQ \tag{6.1}$$

Where:

- Q_1 is the first quartile;
- Q_3 is the third quartile;
- IQ is the interquartile range.

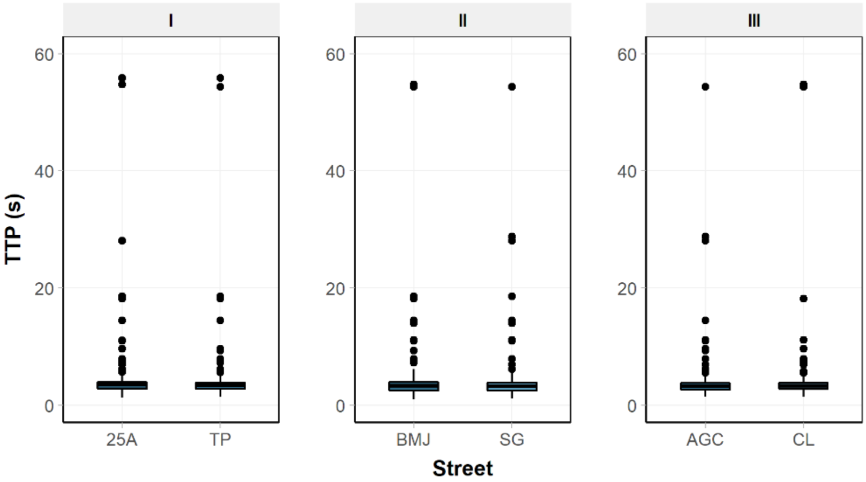


Figure 6.6 – Boxplot of TTP as a function of street scenario, per group of participants.

Satterthwaite's tests showed significant effects of vehicle's movement condition, F(8, 1566.42) = 203.93, $p < 0.01$ and the scenario × condition interaction, F(36, 1560.03) = 2.79, $p < 0.01$. There was no effect of the street scenario, F(5, 267.63) = 1.00, $p = 0.42$. Figure 6.7 shows the TTP registered for every group of participants and respective road scenarios, discarding the original dataset's general outliers. It is possible to note similar values and distribution of the TTP between all the considered street scenarios.

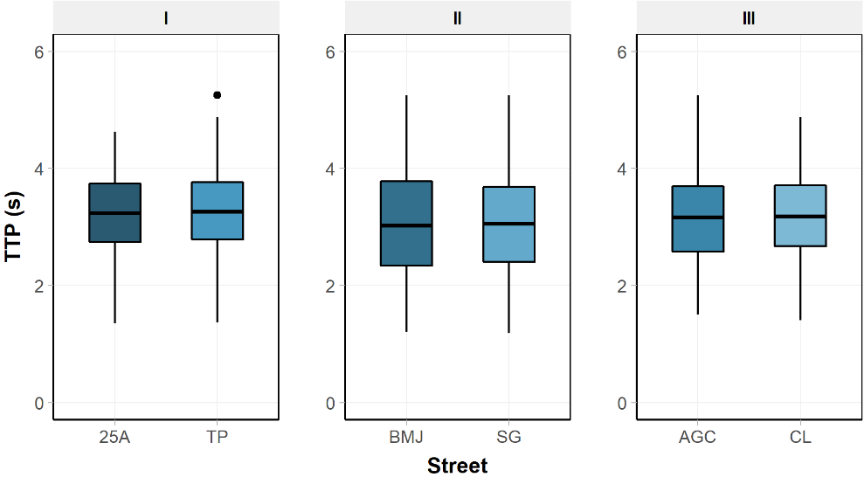


Figure 6.7 – Boxplot of TTP without general dataset's outliers, as a function of street scenario, per group of participants.

Although there were no significant differences between the TTP values observed in all the street scenarios, the next step was to assess which factors related to the characteristics of the road and pedestrian's infrastructure of the simulated streets and the participants' demographic characteristics could affect the TTP. Following the method used in Chapter 2, the variables considered on TTP model were those presented in Table 6.1 (age and sex of participants), in Table 6.2 (the length of the crosswalk, the average width of the lanes, the width of the street to park, the average width of the sidewalks, and width of the crosswalk), with exception of (1) the number of lanes due to its low variability, and (2) the vehicles' mean approaching speed.

The statistical summary of the quantitative variables used in the modelling analysis of TTP presented in Table 6.4 shows that, in general, the TTP ranged from 1.19 to 5.26 s (m = 3.16 s; sd = 0.73 s). The natural logarithm of the TTP (logTTP) was also considered in this part of the modelling task due to the previously referred deviations from homoscedasticity and skewness of TTP distribution. 1639 observations were considered, of which 608 (37.10 %) were crossings done by female participants, and the remaining 1031 (62.90 %) were done by male participants.

Table 6.4 – Statistical summary of the quantitative variables considered to model the TTP.

Variable	**Abbreviation**	**Unit**	**Min**	**Q_1**	**Median**	**Mean**	**Q_3**	**Max**	**SD**	**Coef. of Variation**
Time-to-passage	TTP	s	1.19	2.66	3.19	3.16	3.74	5.26	0.73	0.23
Logarithm of TTP	logTTP	s	0.17	0.98	1.16	1.12	1.32	1.66	0.25	0.22
Vehicles' mean speed	CarSpeed_mean	km/h	12.38	13.37	15.15	15.65	18.33	27.23	2.66	0.17
Length of the crosswalk	Cross_length	m/m	7.03	7.13	7.85	8.71	9.96	12.50	1.86	0.21
Average width of the lanes	Lane_width	m/m	2.56	2.87	3.26	3.11	3.32	3.57	0.34	0.11
Width of the street to park	Parking_width	m/m	1.92	2.34	5.17	5.50	7.15	10.12	2.95	0.54
Average width of the sidewalk	Sidewalk_width	m/m	1.32	1.52	2.96	2.78	4.11	4.17	1.18	0.42
Width of the crosswalk	Cross_width	m/m	3.00	3.04	3.54	3.96	5.12	5.35	0.96	0.24
Participants' age	PartAge	year	21	24	28	28.01	32	39	4.97	0.18

The Pearson correlation analysis revealed that the mean speed of the vehicles along the encounters was the variable with the highest correlation with TTP (ρ = - 0.21), even though it was a low correlation ($|\rho| < 0.30$). As a first step of the model fitting, the null model, *i.e.*, the model with no covariates, was fitted (Expression 6.2).

$$\log TTP_{s,i} = \beta_{0,i} + b_{0,i} + \varepsilon_{s,i}, \tag{6.2}$$

$b_{0,i} \sim N(0, \sigma_P^2)$, $\varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2)$, s = 1st, ..., 45th participant, and i = 1st, ..., 1639th observation

This model is useful for deciding whether a random-effects model might be appropriate for the data. Since $\sigma_P^2 = 0.0085$ and $\sigma_\varepsilon^2 = 0.2178$, only 3.75 % (0.0085 / (0.2178 + 0.0085)) of the data variation is explained by allowing the intercept to vary across the participants, indicating that unobserved heterogeneity of logTTP among the participants may not be captured by using a random-intercept model. In this way, a simple linear regression was fitted to identify the variables with a significant effect on logTTP. The first iteration of modelling task considered all the variables previously described (see Expression 6.3).

$$\log TTP_i = \beta_0 + \beta_1 Cross\_length + \beta_2 Lane\_width + \beta_3 Parking\_width + \beta_4 Sidewalk\_width + \beta_5 Cross\_width + \beta_6\ CarSpeed\_mean + \beta_7 PartAge + \beta_8 PartGen + \varepsilon_i, \tag{6.3}$$

$\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, i = 1st, ..., 1639th observation

The results obtained for the first iteration of the TTP model are presented in Table 6.5. Among all the considered variables, only the vehicles' mean speed was found to be statistically significant (β = - 0.0122, $p < 0.01$). Although they are not the final results of the TTP model, it is shown that the higher the mean approaching speed of the vehicles, the lower the logTTP, and thus the riskier the crossing decision made by pedestrians.

Table 6.5 – Results of the 1st iteration of the TTP model.

	β	**Std. Error**	**p-value**
Intercept	1.4319	0.0788	< 0.01
Cross_length	- 0.0074	0.0037	0.05
Lane_width	0.0281	0.0176	0.11
Parking_width	0.0006	0.0028	0.82
Sidewalk_width	0.0070	0.0065	0.28
Cross_width	- 0.0220	0.0022	< 0.01
CarSpeed_mean	- 0.0009	0.0013	0.47
PartAge	1.4319	0.0788	< 0.01
PartGen (ref. Female)			
Male	0.0254	0.0129	0.05
ε		0.24	
R^2		0.07	

The iterative process continued with the removal of the Parking_width variable (p = 0.82), and so on, until the last (5th) iteration, where only the CarSpeed_mean, PartGen, and Cross_length variables were considered (see Expression 6.4). The results of the final iteration of the TTP model are presented in Table 6.6.

$$\log TTP_i = \beta_0 + \beta_1 Cross\_length + \beta_2 CarSpeed\_mean + \beta_3 PartGen + \varepsilon_i, \tag{6.4}$$

$$\varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2),\ i = 1^{st}, \ldots, 1639^{th} \text{ observation}$$

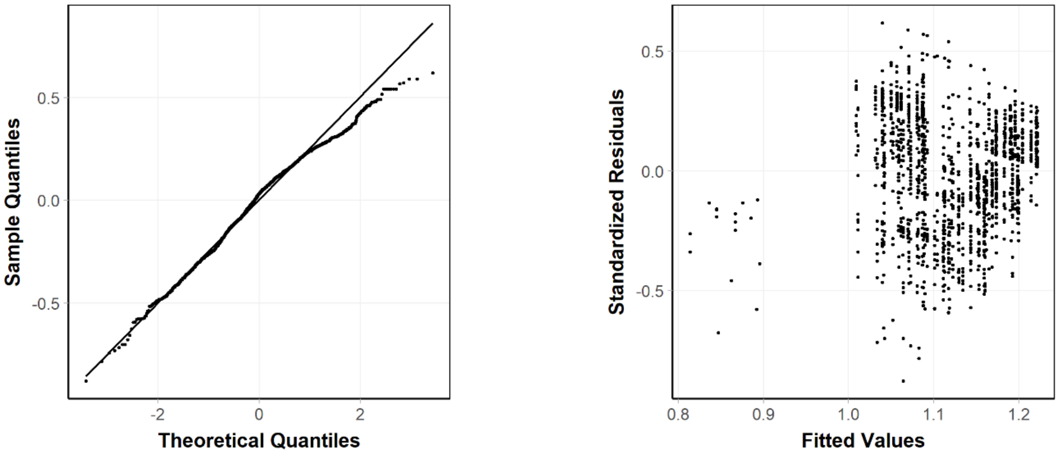
The low value of the coefficient of determination ($R^2 = 0.07$) shows that the linear regression model is not the best technique to explain how the logTTP varies with the considered variables. However, this analysis aimed to identify the variables with a significant effect on logTTP and not explain the variation of the logTTP.

The effect of the vehicle's mean speed on logTTP (β = - 0.0221) seems to be much bigger than the one verified in the Chapter 2. However, it was almost the same. The crosswalk length also had a significant and negative effect on logTTP (β = - 0.0088) and, thus, on pedestrian safety. The larger the distance the participants had to walk crossing the road, the riskier the participant's decision. On the other hand, despite having crossed more times than female participants, men had safer decisions (β = 0.0306).

Table 6.6 – Results of the final iteration of the TTP model.

	β	**Std. Error**	**p-value**
Intercept	1.5272	0.0438	< 0.01
Cross_length	- 0.0088	0.0032	0.01
CarSpeed_mean	- 0.0221	0.0022	< 0.01
PartGen (ref. Female)			
Male	0.0306	0.0122	0.01
ε		0.24	
R^2		0.07	

Furthermore, based on the Normal quantile-quantile (Q-Q) plot, it was assumed that there are no significant deviations from the normality assumption (Figure 6.8 (a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 6.8 (b)).



(a) (b)

Figure 6.8 – Verification of the assumptions for the TTP model: (a) Q-Q plot; (b) Standardized residual versus fitted values.

6.3.3 Minimum time-to-collision

Such as in TTP analysis, the first step to analyse the TTC_{min} was the construction of an LMM, considering random effects for the *participant* and fixed effects for the *vehicle's movement condition* and the *street scenario*.

Like for the TTP modelling task, a few outliers were identified (Figure 6.9). The existence of those points is explained by a few situations in which the participants started to cross when the vehicle was almost stopped, which greatly increased TTC_{min}. To deal with the referred deviations, the outliers of the TTC_{min} were removed using Expression 6.1 but now switching TTP by TTC_{min}.

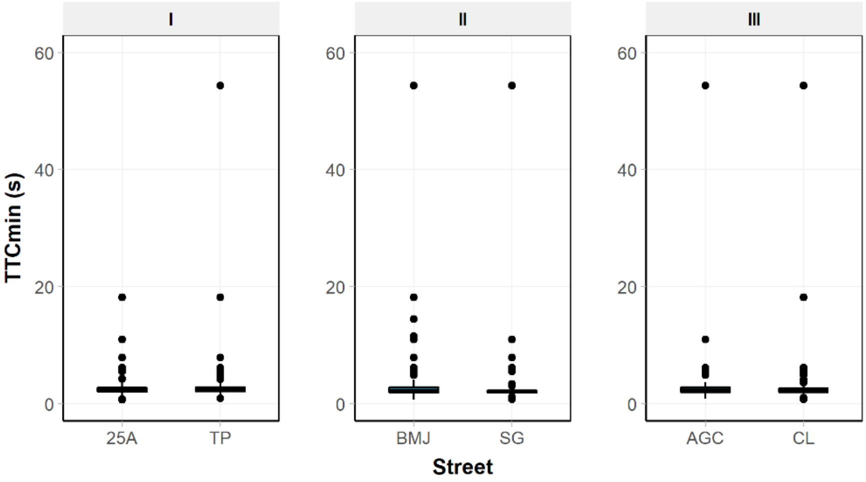


Figure 6.9 – Boxplot of TTC_{min} as a function of street scenario, per group of participants.

Satterthwaite's tests showed significant effects of vehicle's movement condition, F(8, 1729.7) = 17.99, $p < 0.01$, but not of street, F(5, 162.00) = 0.72, $p = 0.61$, and the scenario × condition interaction, F(36, 1726.90) = 1.13, $p = 0.27$. Figure 6.10 shows the TTP registered for every group of participants and respective road scenarios, discarding the general outliers of the original dataset.

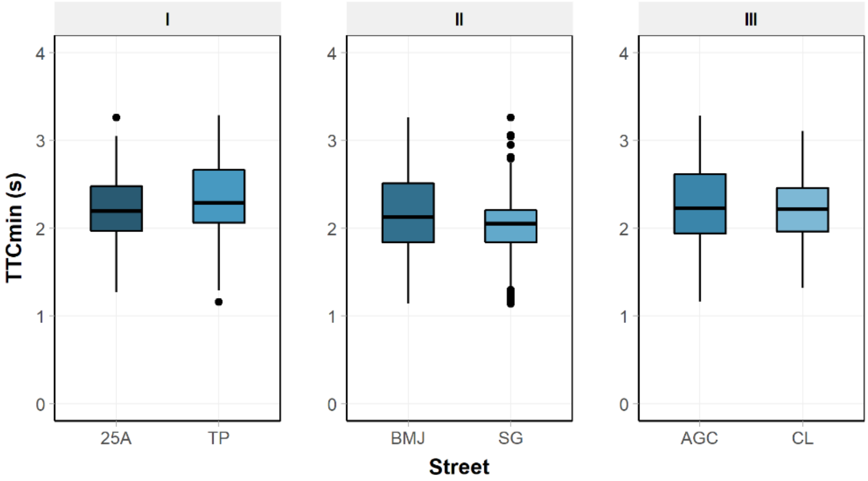


Figure 6.10 – Boxplot of TTC_{min} without general dataset's outliers, as a function of street scenario, per group of participants.

Following the same procedure used in TTP analysis, the next step was an attempt to understand if there were some factors related to the characteristics of the road and pedestrian infrastructure of the simulated streets and the participants' demographic characteristics, explaining the variation of TTC_{min}. The same covariates considered on the TTP model were here considered. The statistical summary of the quantitative variables used in the modelling analysis of TTC_{min} presented in Table 6.7 shows that, in general, the TTC_{min} ranged from 1.14 to 3.29 s (m = 2.21 s; sd = 0.44 s). 1530 observations were considered, of which 572 (37.39 %) were crossings done by female participants, and the remaining 958 (62.61 %) were done by male participants.

The Pearson correlation analysis revealed that the length of the crosswalk was the variable with the highest correlation with TTC_{min} (ρ = - 0.19), even though it was a low correlation ($|\rho| < 0.30$). Then, the null model was fitted (Expression 6.5).

$$TTC_{min\ s,i} = \beta_{0,i} + b_{0,i} + \varepsilon_{s,i}, \tag{6.5}$$

$b_{0,i} \sim N(0, \sigma_P^2)$, $\varepsilon_{s,i} \sim N(0, \sigma_\varepsilon^2)$, s = 1st, ..., 45th participant, and i = 1st, ..., 1530th observation

Table 6.7 – Statistical summary of the quantitative variables considered to model the TTC_{min}.

Variable	Abbreviation	Unit	Min	Q_1	Median	Mean	Q_3	Max	SD	Coef. of Variation
Minimum time-to-collision	TTC_{min}	s	1.14	1.94	2.20	2.21	2.48	3.29	0.44	0.20
Vehicles' mean speed	CarSpeed_mean	km/h	12.38	13.37	15.15	15.57	18.33	27.23	2.48	0.16
Crosswalk length	Cross_length	m/m	7.03	7.13	7.85	8.72	9.96	12.50	1.88	0.22
Lanes' mean width	Lane_width	m/m	2.56	2.87	3.26	3.11	3.32	3.57	0.34	0.11
Parking width	Parking_width	m/m	1.92	2.34	5.17	5.50	7.15	10.12	2.93	0.53
Sidewalks' mean width	Sidewalk_width	m/m	1.32	1.52	2.96	2.80	4.11	4.17	1.18	0.42
Crosswalk width	Cross_width	m/m	3.00	3.04	3.54	3.97	5.12	5.35	0.96	0.24
Participants' age	PartAge	year	21	24	28	28.05	32	39	5.02	0.18

Since $\sigma_P^2 = 0.0001$ and $\sigma_\varepsilon^2 = 0.0357$, only 2.79 % (0.0001 / (0.0357 + 0.0001)) of the data variation is explained by allowing the intercept to vary across the participants, indicating that unobserved heterogeneity of TTC_{min} among the participants may not be captured by using a random-intercept model.

A simple linear regression was then fitted to identify the variables with a significant effect on TTC_{min}. The first iteration of modelling task considered all the variables previously described (see Expression 6.6).

$$TTC_{min,\,i} = \beta_0 + \beta_1 Cross\_length + \beta_2 Lane\_width + \beta_3 Parking\_width + \beta_4 Sidewalk\_width + \beta_5 Cross\_width + \beta_6\ CarSpeed\_mean + \beta_7 PartAge + \beta_8 PartGen + \varepsilon_i, \tag{6.6}$$

$$\varepsilon_i \sim N\ (0, \sigma_\varepsilon^2),\ i = 1^{st}, \ldots, 1530^{th} \text{ observation}$$

The results obtained for the first iteration of the TTC_{min} model are presented in Table 6.8. Again, only the vehicles' mean speed was found to be statistically significant (β = - 0.0261, p < 0.01). The effect of the vehicle's mean speed on TTC_{min} (β = - 0.0221) was less expressive than that verified in Chapter 2. The crosswalk length also had a significant and negative effect on TTC_{min} (β = - 0.0463) and, thus, on pedestrian safety. On the other hand, despite having crossed more times than female participants, the TTC_{min} model also shows that men had safer decisions (β = 0.0567).

The iterative process continued with the removal of the Lane_width variable (p = 0.97), and so on, until the last (5th) iteration, where only the CarSpeed_mean, PartGen, and Cross_length variables were considered (see Expression 6.7). The results of the final iteration of the TTP model are presented in Table 6.9.

$$TTC_{min,\,i} = \beta_0 + \beta_1 Cross\_length + \beta_2 CarSpeed\_mean + \beta_3 PartGen + \varepsilon_i, \tag{6.7}$$

$$\varepsilon_{s,i} \sim N\ (0, \sigma_\varepsilon^2),\ i = 1^{st}, \ldots, 1530^{th} \text{ observation}$$

The effect of the vehicle's mean speed on TTC_{min} (β = - 0.0221) was less expressive than that verified in Chapter 2. The crosswalk length also had a significant and negative effect on TTC_{min} (β = - 0.0463) and, thus, on pedestrian safety. On the other hand, despite having crossed more times than female participants, the TTC_{min} model also shows that men had safer decisions (β = 0.0567).

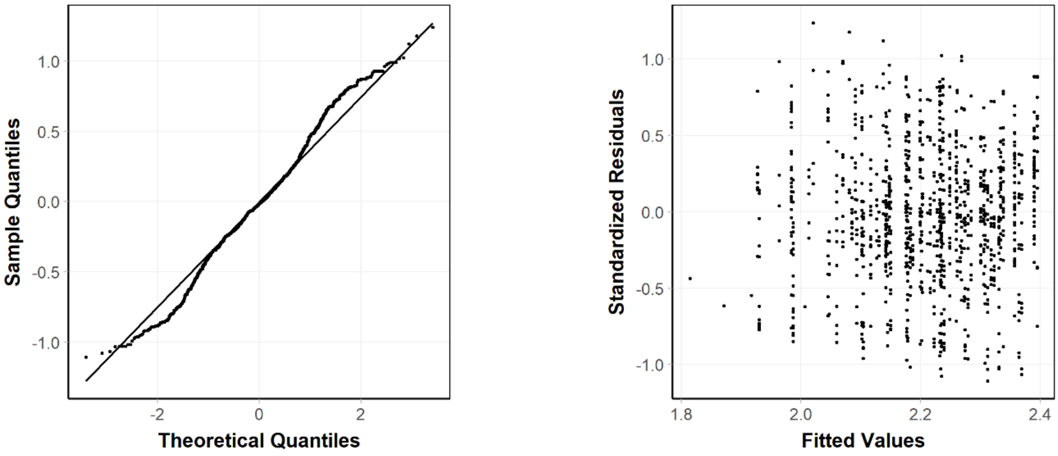
Table 6.8 – Results of the 1st iteration of the TTC_{min} model.

	β	**Std. Error**	**p-value**
Intercept	3.3362	0.4499	< 0.01
Cross_length	- 0.1167	0.0689	0.09
Lane_width	0.0019	0.0580	0.97
Parking_width	- 0.0540	0.0554	0.33
Sidewalk_width	- 0.0324	0.0308	0.29
Cross_width	0.1871	0.1772	0.29
CarSpeed_mean	- 0.0261	0.0044	< 0.01
PartAge	- 0.0032	0.0024	0.18
PartGen (ref. Female)			
Male	0.0450	0.0243	0.06
ε		0.43	
R^2		0.07	

Table 6.9 – Results of the final iteration of the TTC_{min} model.

	β	**Std. Error**	**p-value**
Intercept	2.9875	0.0861	< 0.01
Cross_length	- 0.0463	0.0059	< 0.01
CarSpeed_mean	- 0.0262	0.0044	< 0.01
PartGen (ref. Female)			
Male	0.0567	0.0228	0.01
ε		0.43	
R^2		0.06	

Based on the Normal quantile-quantile (Q-Q) plot, it was assumed that there are no significant deviations from the normality assumption (Figure 6.11 (a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 6.11 (b)).



(a) (b)

Figure 6.11 – Verification of the assumptions for the TTC$_{min}$ model: (a) Q-Q plot; (b) Standardized residual versus fitted values.

6.4. Discussion

As mentioned in section 6.2.6, the analysis carried out in this chapter can be divided into two distinct parts: a first one allowing the general comparison of the participants' decision-making between all the virtual scenarios used, in terms of the variables covered in Chapter 5 (percentage of crossings, percentage of crashes, crossing start time and TTP) added to TTC$_{min}$; a second one that, according to the application of a method very similar to that used in Chapter 2, allows the identification of factors related to the demographic characteristics of the participants, to the characteristics of the road and pedestrian infrastructure of the simulated streets, and the vehicle's approaching speed with influence on TTP and TTC$_{min}$.

Regarding the first part of the analysis, the LMMs built to analyse the effect of the vehicle approaching movement and street scenario (and the interaction between them), showed that the crossing was mainly based on the movement conditions of the vehicle.

As it is an aspect addressed and well explored in the previous chapters, with the conclusions pointing to the importance of vehicle kinematics in the participants' decision-making, the effect of vehicle's movement conditions was no longer explored. However, being a variable with a significant impact on all the considered indicators confirms such conclusions. In turns, the results of the LMMs constructed to assess the percentage of crossings, the percentage of crashes, the crossing start time, TTP, and TTC_{min} revealed that the street scenario does not have a significant influence on the participants' crossing decision-making.

Regarding the second part of the analysis, the first evidence is that the significant variables for both TTP and TTC_{min} are the same, but with different magnitudes. The justification for this is the moderately strong correlation between the two dependent variables (ρ = 0.67). The results obtained in the analysis of both indicators, TTP and TTC_{min}, confirmed the relevance of the role of vehicle speed in pedestrian safety and crossing decision-making referred in studies such as Granié *et al.* (2014), Liu and Tung (2014), Sucha *et al.* (2017), and Várhelyi (1998). The tendency of the vehicle's approaching speed to lead to lower TTP and TTC_{min} values allows one to conclude that, in addition to leading to more risky crossing decisions, the higher the vehicle's approaching speed, the greater the probability of a crash to happen.

It should be noted that, in the TTC_{min} model built with field observations data, the average approaching speed of vehicles to the crosswalk did not emerge as a significant variable. However, it seems logical that this variable can impact the TTC_{min}, which, in turns, corresponds to an indicator of the severity of the vehicle-pedestrian encounter, since higher vehicle's approaching speeds may indicate an increase of the probability of more severe encounters to occur, *i.e.*, encounters where an accident could happen.

Comparing the magnitudes of the vehicle's approaching speed's effects, it is possible to note a considerable difference between the TTP model constructed in this chapter and the TTP model of Chapter 2. The fact that the magnitude of the effect of the vehicle's approaching speed is bigger in the linear regression made for the data obtained through the virtual environment experiments may be due to the smaller number of vehicle's movement conditions characterized. If, on the one hand, virtual environments allow great control over the variables considered in a study, on the other hand, in some situations, they do not allow to simulate the great diversity of situations occurring in the real world. However, expanding the number of conditions related to the vehicle's movement would make the experimental task unaffordable for the participants, increasing its duration and the demand of participants' concentration, thus compromising the results.

Allowing the control of the participants' sample is another advantage of performing a study in a virtual environment. In this case, with a balanced sample in terms of the participants' age and sex, it was possible to verify that male participants made safer decisions than females despite crossing more often. This may seem inconsistent; however, it can be easily explained by the participants' speed. With a distance of 3 m from the beginning of the presentation of the stimulus to the beginning of the crossing, the male participants, with higher speeds (m = 1.35 km/h; sd = 0.57 km/h), reached the crosswalk when the vehicle was further away from it, while female participants, with lower speeds (m = 1.33 km/h; sd = 0.49 km/h), arrived at the crosswalk when the vehicle was already close, which consequently corresponded to situations where smaller TTP and TTC_{min} were observed. In this way, it is not possible to confirm the studies' conclusions that point to female pedestrians as the more conservative when crossing the road (Hamed, 2001; Holland and Hill, 2007; Moyano Díaz, 2002; Papadimitriou *et al.*, 2016b).

The length of the crosswalk was the other variable with a significant effect on TTP and TTC_{min}. The impact of this variable was unfavourable to pedestrian safety. The longer the crosswalk's length, the riskier was the participants' decision, since smaller TTP were recorded, and more severe was the encounter with the vehicle (smaller TTC_{min} were observed). The significant impact of this variable on pedestrian safety had already been revealed in Chapter 2, through the vehicle's approaching speed model, in the sense that "larger roads, with wider lanes and longer crosswalks, provide favourable conditions for the practice of higher speeds by drivers"(Sucha *et al.*, 2017; Turner *et al.*, 2006; Zegeer *et al.*, 2006).

However, the models developed in the present chapter show that this variable's effect goes beyond the impact on the vehicle's approaching speed. In these experiments, the speed was a controlled variable, independent from the length of the crosswalk. This effect may be due to greater hesitation in crossing decision-making. In some situations where the distance to be crossed was greater, participants could take more time to decide to cross, and when they decided to do it, the vehicle was closer to them.

The effect of this variable, such as others already covered in this chapter and Chapter 2, can be more deeply assessed in a future study to be carried out in a virtual environment, if, for the same scenario, *i.e.*, for the same street, the characteristic in question could be exclusively varied throughout the entire experimental procedure. This study would not require an extensive sample of participants, given the number of repetitions of each stimulus, and it would be more effective in a search for factors related to the road characteristics with an effect on participants' crossing decision.

TTP and TTC_{min}, as shown in Chapter 2, are not linearly explained. However, as previously mentioned, explaining the variation of both indicators was not the objective of this work. The two linear regression models allowed to compare the results of this chapter with the ones of Chapter 2. Nevertheless, in an almost obvious way, the ideal situation regarding the achievement of the equal models between the two chapters, concerning each indicator, was not verified, not even in terms of the number of explanatory variables with a significant effect on dependent variables. This can be explained by the limited number of vehicle's approaching movement conditions depicted. Ideally, the number of movement conditions should be much higher because that is the only way to represent what happens on a real crosswalk accurately. However, as already mentioned and explained, this would be methodologically unaffordable.

It would also be interesting that more vehicles and virtual pedestrians were integrated into the simulated environment in future work. Instead of a single approaching vehicle, there would be several ones with different and varying distances between them. This could allow to make a more precise and detailed evaluation of the effect of motorized and pedestrian traffic volumes considered in Chapter 2.

6.5. Conclusions

The main objective of the analysis presented in this chapter was to complement the work carried out in Chapter 2, where risk factors in the vehicle-pedestrian interaction and crossing decision-making process were identified using data collected in a real environment. Being the last analysis done in this doctoral project, it was developed considering all the work presented in the previous chapters, from Chapter 2, concerning the variables and analysis techniques covered, to Chapter 5, regarding the experimental design and used procedure.

The models constructed revealed evidence of the important role of the vehicle's approaching speed in pedestrians' crossing decision and in the severity of the encounters between those vulnerable road users and vehicles. Furthermore, of the remaining variables considered, only the sex of the participants and the length of the crosswalk proved to have a significant effect on both considered indicators, TTP and TTC_{min}.

Male participants had less risky decisions and less severe encounters with vehicles due to their higher walking speed. Longer crosswalks seem to be negative to pedestrian safety.

Despite the street features as the crosswalk length being a significant variable to pedestrians' crossing decision and to the severity of the encounters between pedestrians and vehicles, the street scenario itself was not. The street could not significantly affect the percentage of crossings, the percentage of crashes, the crossing start time, the TTP, and the TTC_{min}.

In addition to the contribution related to the identification of risk factors for the task of crossing the road, this work has a methodological contribution that can be followed in future studies to be carried out in a simulator, showing that the implementation of extremely realistic scenarios may not be relevant, because there are factors having an effect in the real world pedestrian's crossing decision and interaction with vehicles which are difficult to perceive in a simulation, at least with the setup used in this study.

7. MAIN CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORKS

7.1. Conclusions

The main objective of this doctoral project was the identification and analysis of factors with influence on the risk to which pedestrians are subject to, when crossing the road, with a particular focus on their crossing decision-making and their interaction with vehicles approaching the crosswalk.

The work consisted of a compilation of five studies which were carried out considering different aspects of the pedestrian road crossing task, aiming to assess the influence of the pedestrians' demographic factors the road and crossing infrastructure, and the traffic characteristics on crossing decision-making and vehicle-pedestrian interaction (Chapter 2 and Chapter 6), to analyse the effect of vehicles' noise and the auditory cues, as well as vehicle kinematics, on pedestrian crossing decision-making (Chapter 3 and Chapter 4), and to evaluate the implementation of a more realistic approach for studying pedestrian crossing behaviour using virtual environments (Chapter 5 and Chapter 6).

Although each chapter has its own section of conclusions, a summary is presented here for a general overview.

7.1.1 The effect of the vehicle's noise and the relevance of auditory cues on pedestrians' crossing decision-making

Chapter 3 presented a preliminary experimental work in the simulator where a small sample of participants performed a crossing decision task standing at the same position the entire experiment. Three types of stimuli were presented regarding the auditory condition: the gasoline combustion vehicle, the electric vehicle, and the no sound condition. The results did not show an evident effect of the sound on the participants' crossing decision-making. Although the response time and TTP values varied significantly between the presented auditory conditions, the percentage of responses did not.

Furthermore, the human error associated with vehicle movement acquisition when collecting the sound samples may have influenced the participants' responses.

Chapter 4 reported a study that extended the one presented in Chapter 3 to clarify the role of the auditory cues on pedestrians' crossing decision-making. A similar experimental approach was used. A bigger set of vehicle's movement conditions were included, with only two types of auditory conditions (gasoline combustion vehicle and no sound condition). Besides, it was performed by a larger sample of participants to increase the robustness of the results. The results confirmed that the sound emitted by the vehicle is not relevant to the pedestrians' crossing decision-making since no significant difference was found between the auditory conditions in terms of percentage of crossings, response time, and TTP.

This conclusion is valid when pedestrians face situations like the one considered in the experiment, *i.e.*, when pedestrians cross a road with perfect visibility conditions of the approaching vehicle.

7.1.2 The effect of the vehicle's kinematics on pedestrians' crossing decision-making

The influence of vehicle's kinematics in pedestrians' crossing decision-making was evaluated practically throughout the entire investigation.

The analysis of the crossing decision and the severity of the encounter between pedestrians and vehicles in a set of twelve distinct crosswalks found that the vehicles' approaching speed affects the pedestrians' crossing decision, as analysed through TTP. Higher vehicle speeds lead pedestrians to make riskier decisions (Chapter 2).

This conclusion was confirmed through a study carried out in the simulator using six different virtual scenarios (Chapter 6). As in the study presented in Chapter 2, the results showed that vehicles' speed influences pedestrians' crossing decision-making, leading them to start crossing with lower TTPs. Nevertheless, in the study performed in a virtual environment, the vehicle's approaching speed also affected the severity of the encounters between vehicles and pedestrians. The higher the average speed of approach of the vehicles, the closer the hit was to happen, since lower values of TTC_{min} were verified.

In Chapter 3, three conditions related to the vehicle's approach speed pattern were presented: Constant, Slow Down, and Stop patterns. The results showed that the vehicle's approaching speed pattern influenced the observed percentage of crossings and the response time. The participants took longer to decide, but they crossed more often when the vehicle stopped or slowed down than when they passed at a constant speed. However, TTP was not affected by the vehicle's speed pattern leading to the conclusion that the decision to cross pedestrians is decisively based on the vehicle's combination of speed profile and distance, with a relatively greater importance of the latter being observed.

In the study presented in Chapter 4, with the implementation of a greater number of conditions related to the vehicle's approach movement, the conclusions regarding the importance of the vehicle's speed pattern were strengthened. Furthermore, it was possible to evaluate the influence of the vehicle's speed and initial distance on the participants' crossing decision-making. The greater the initial distance, the greater the percentage of crossings, the greater the response times, and, due to being directly related, the greater the TTP.

Regarding the vehicle's initial speed, the opposite was true. The higher the vehicle's initial speed, the lower the percentage of crossings. Another important aspect is the interaction effect between the initial speed and the vehicle's speed pattern. This interaction causes the response time to decrease with the increase of the vehicle's initial speed only in the stimuli referring to the Constant pattern, having increased when the vehicle stopped or slowed down. For an initial speed of 20 km/h, the TTP on the Slow Down pattern was lower than in the Constant, but for 30 km/h, the opposite was true. Also, the TTP was lower for the Stop when vehicle started approaching the crosswalk at 20 km/h, but the opposite was true for the Slow Down pattern. For 30 km/h initial speed, most crossings happened later in the trial, when the vehicle was already at a lower speed (Stop pattern), making the TTP to be higher.

Chapter 5 strengthened the conclusions of Chapter 4 about the importance of vehicle kinematics to the participants' crossing decision-making throughout the adoption of an experimental approach were the participant crossed a semi-virtual crosswalk walking along it. In general terms, the results obtained with the dynamic experimental approach did not differ from those of the static approach, except for the response time or crossing start time. This difference was explained by the distance of 3 m that the participants had to walk between the beginning of the trial and the arrival at the crosswalk in the dynamic approach.

Summarizing, the vehicles' approaching speed affects the pedestrians' crossing decision-making and their interaction with vehicles on crosswalks, negatively impacting pedestrian safety. However, pedestrians base their decision also on the vehicle's distance evolution during the approaching time. What pedestrians perceive in terms of vehicles' approaching speed and distance determines their crossing decision.

7.1.3 The effect of the pedestrians' demographic, the road and pedestrian infrastructure, and the traffic characteristics on crossing decision-making and vehicle-pedestrian interaction

Differing on the data collection methods, Chapter 2 and Chapter 6 had the main goal of assessing the influence of the pedestrians' demographic, the road and pedestrian infrastructure, and the traffic characteristics on crossing decision-making and vehicle-pedestrian interaction.

In the study presented in Chapter 2, which is based on the data gathered from a total of 459 observations of pedestrian-vehicle encounters in 12 real-world crosswalks, the results show a negative effect of the vehicle's mean speed, as mentioned before, and a positive impact of the transversal width of the street intended for parking spaces on TTP, and thus on the safety of the pedestrians' crossing decision. If, on the one hand, higher vehicle speeds compromise pedestrian safety, the parking spaces' width has the opposite effect. The reason for this last effect has not been studied so far. A plausible explanation is a possible greater level of caution and prudence felt by pedestrians motivated by parked vehicles, which can block the view for oncoming vehicles.

The TTC_{min} analysis revealed a positive effect of the motorized and the pedestrian traffic volumes on the severity of pedestrian-vehicle encounter, *i.e.*, higher motorized and pedestrian traffic lead to safer encounters. Higher pedestrian traffic volumes can increase the drivers' alertness. Greater motorized traffic volumes can affect pedestrian caution. Furthermore, depending on road capacity, higher motorized traffic volumes can make high speeds impossible to be practiced by drivers. The crosswalk width has the opposite effect. Wider crosswalks allow for more unsafe crossings, possibly due to a greater sense of comfort and safety felt by pedestrians, leading to an excessive level of confidence during the crossing, which may jeopardize their safety.

The fact that the vehicles' approaching speed has affected the pedestrians' crossing decision-making led to the analysis of the factors that influenced this variable and, indirectly, the pedestrians' safety. The results showed that larger roads, with wider lanes and longer crosswalks, provide favourable conditions to the practice of higher speeds. In the same direction as the results of the analysis of TTC_{min}, higher pedestrian traffic volumes lead to lower vehicles' approaching speeds. The distance to the closest bus stop was the other variable that significantly affected vehicles' approaching speed. The greater the distance from the crosswalk to a bus stop, the lower the vehicle's mean approaching speed. This result can be explained by the creation of a visual block delaying pedestrians' detection by the drivers. Very voluminous objects as buses, other pedestrians, and even the bus stop, may turn the pedestrians' detection harder for drivers who do not adapt their speed.

The models of TTP and TTC_{min} developed in the study presented in Chapter 6, which is based on the data gathered from a virtual environment conducted to 45 participants using 6 different scenarios, had the particularity to have the same significant variables. They confirmed the important role of the vehicle's approaching speed in pedestrians' crossing decision and the severity of the encounters between both. Also, the sex of the participants and the length of the crosswalk showed to have a significant effect on both considered indicators, TTP and TTC_{min}. Male participants made less risky decisions and had less severe encounters with vehicles due to their higher walking speed. Longer crosswalks seem to be harmful to pedestrian safety.

Combining the results of both studies, the importance of vehicles' speed for pedestrian safety is evident. In addition to being an essential variable in crossing decision making, as mentioned in the previous section, vehicles' approaching speed is also one factor that most affects pedestrian safety. Safer crosswalks are those where vehicles travel at low speeds. Reducing the roads' width, shortening the crosswalks' length, and placing the crosswalks distanced from bus stops can be effective measures to improve pedestrians' safety conditions. Reduce the crosswalk's width and implementing perpendicular parking spaces can also be favourable to pedestrians' safety.

7.2. Recommendations for future works

The development of a simulator for the analysis of pedestrian behaviour and risk opens the way to the execution of several studies in the future. Regarding the simulator use, several conclusions are presented concerning the methodology to follow which should be considered in future works:

- The type of experimental approach (Static or Dynamic) to be applied must be chosen according to the goal of the study to be evaluated. The advantages and disadvantages of each one of these methodologies must be considered taking mainly into account that: (i) the dynamic approach is more naturalistic and allows not only for the evaluation of the pedestrians' decision-making but also for parameters related to their gait and movement; and (ii) the static approach merely allows for the analysis of decision-making, but, in turn, the experiences that follow this approach are quicker performed by the participants.
- The vehicles' speed variation during the approaching to the crosswalk should be considered in all the studies using the simulator since it is an essential cue used by pedestrians in crossing decision-making.
- The sound produced by the vehicle's movement is not essential for situations in which the vehicle approaches in a straight line and without obstacles to the participant's vision; however, its consideration makes the experience more realistic.
- The size of the sample of participants in each study should be such that it allows a suitable statistical consistency of the data, considering that participants may vary substantially in their behaviour (as shown by the differences between the most impulsive and the most conservative participants).

As referred along this document, future work may pass by:

- The analysis of the effect of sound on pedestrians' crossing behaviour considering other types of trajectories and obstacles to the participants' vision, in order to determine the general importance of the auditory cues to pedestrians' crossing decision-making. This is important considering that low noise vehicles are increasingly common.

- To integrate more vehicles and pedestrians into the simulated environment to assess the effect of motorized and pedestrian traffic volumes and the interaction between pedestrians on their crossing behaviour.
- To complement the results of the analysis carried out in Chapter 2 and Chapter 6, which aimed to identify influence of several factors on pedestrian crossing decision-making and interaction with the approaching vehicles, using a single street virtual scenario where specific characteristics were varied during the experiment's trials. Furthermore, more data should be gathered from real crosswalks located at other streets in the same cities or others. This would allow a deeper analysis of factors regarding sociocultural characteristics, increasing the variability of the roads and pedestrian infrastructure characteristics. It would allow the consideration of other variables which were not considered in these studies, such as the number of lanes, the land use and the road pavement, among others. The increase in the number of observations would also give even more robustness to the global analysis results.

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APPENDIX

Appendix I – Summary table of all the cited studies about pedestrians' road crossing safety

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Amoh-Gyimah *et al.* (2016)	Accident and Census data	-	Crashes frequency and Injury severity.	Demographic, Socio-economic, Land use characteristics and Exposure.
Ashmead Daniel *et al.* (2005)	Controlled experiments (Semi-controlled naturalistic experiments)	12 participants	Waiting time; Probability of a dangerous crossing attempt; Gap duration; and Number of crossings.	Traffic volume; Group of pedestrians (blind and sighted); Position of nearest vehicle; and Number of yields.
Barton *et al.* (2013)	Surveys/Controlled experiments	85 participants	Detection distance; Approach decision; and Position determination.	Pedestrian age; Pedestrian sex; and Vehicle speed.
Barton *et al.* (2012)	Surveys/Controlled experiments	50 participants	Detection distance; Approach decision; and Position determination.	Pedestrian age; Pedestrian sex; and Vehicle speed.
Bernhoft and Carstensen (2008)	Surveys (Questionnaires)	1905 participants	Travel pattern; Conditions of importance for walking or cycling; and Behaviour in specific traffic situations (*e.g.*, road crossings).	Pedestrian age and Pedestrian sex.
Cafiso *et al.* (2011)	Field observations (Video recordings)	-	Pedestrian Risk Index (PRI).	Presence and Type of traffic speed calming.
Cavallo *et al.* (2019)	Controlled experiments (Virtual reality experiments - CAVE-based system)	79 participants	Accepted TG and Collisions.	Vehicle speed; Lane; Training group and Testing type.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Cavallo *et al.* (2009)	Controlled experiments (Virtual reality experiments - CAVE-based system)	72 participants	Crossing time; Initiation time; Accepted TG; Safety margin; Unsafe decisions; and Missed opportunities.	Pedestrian age and Vehicle type.
Charron *et al.* (2012)	Controlled experiments (Virtual reality experiments - Screen-based setup)	80 participants	Type of route taken; Information processing; Speed of movement; Risk behaviours.	Pedestrian sex; and Type of condition.
Connelly *et al.* (1998)	Controlled experiments (Semi-controlled naturalistic experiments)	48 participants	Distance gap and Safe distance index.	Crossing time; Vehicle speed; Pedestrian age; and Pedestrian sex.
de Clercq *et al.* (2019)	Controlled experiments (Virtual reality experiments - HMD system)	28 participants	Crossing decision.	Vehicle distance; Yielding and Non-yielding vehicles; Vehicle size; Type of interaction; and Time of interaction.
Deb *et al.* (2017)	Controlled experiments (Virtual reality experiments - HMD system) and Surveys (Questionnaires)	26 participants	Simulation sickness; Quality of the immersion; Presence measure; Usability measure; Collisions; Minimum gap; Number of collisions; walking speed; and Crossing time.	Trial condition; Pedestrian age; and Pedestrian sex.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
Deb, Rahman, *et al.* (2018)	Literature review	-	-	Pedestrian interaction with fully automated vehicles and Existing research approaches for investigating risky pedestrian behaviour.
Deb, Strawderman, *et al.* (2018)	Controlled experiments (Virtual reality experiments - HMD system) and Surveys (Questionnaires)	30 participants	Crossing time; Waiting time; and Pedestrian behaviours.	Interaction features; Visual interaction features; Audible interaction features; Pedestrian age; and Pedestrian sex.
Dietrich *et al.* (2020)	Controlled experiments (Virtual reality experiments - HMD system)	30 participants	Crossing initiation time.	Type of trajectory and Pitch condition.
Dissanayake *et al.* (2009)	Accident data	521 observations	Crashes frequency and Injury severity.	Land use type (proportion by use); and Week and Day time periods.
Dommes and Cavallo (2011)	Controlled experiments (Virtual reality experiments - CAVE-based system)	60 participants	TTA; Crossing time; Safety margin; Missed opportunities; Unsafe crossings; and Walking speed.	Pedestrian age and Vehicle speed.
Dommes *et al.* (2012)	Controlled experiments (Virtual reality experiments - CAVE-based system)	20 participants	Safety margin; Safe decisions; Tight fits; and Unsafe decisions.	Pedestrian age; Vehicle speed; and Training group.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Emerson *et al.* (2013)	Controlled experiments	15 participants	Detection distance and Crossing margin.	Average wind speed; Amplitude modulation depth difference; Hearing loss at 500 Hz; Amplitude modulation depth difference; Vehicle speed; Minimum ambient sound level; and Overall vehicle sound level.
Emerson *et al.* (2011)	Controlled experiments	39 participants	Safety margin; Accepted gaps; Accepted short gaps; and Surges caught.	Sight impairment and Vehicle type.
Ewing and Dumbaugh (2009)	Literature review-based; Accident data	-	Crashes frequency and Injury severity.	Traffic volume; Traffic speed; Traffic conflicts; Urban sprawl; Street network design; Road width; On-street parking; Traffic-calming measures; Access management; Intersection control; Roadside design; and Pedestrian countermeasures.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
Ezzati Amini *et al*. (2019)	Literature review	-	-	Communication between traffic participants; Crossing behaviours of traffic participants; Pedestrian-associated factors influencing crossing behaviours; Environmental and dynamic factors influencing crossing behaviours; and Correlation of crossing behaviours with surrogate safety measures.
Feldstein and Dyszak (2020)	Controlled experiments (Semi-controlled naturalistic experiments and Virtual reality experiments - HMD system)	30 participants	TTC.	Vehicle speed; Experimental procedure; Pedestrian sex; Exposure order; and Body height.
Feldstein and Peli (2020)	Controlled experiments (Semi-controlled naturalistic experiments and Virtual reality experiments - HMD system)	30 participants	TTC.	Vehicle brightness and Experimental procedure.
Feldstein *et al*. (2016)	Controlled experiments (Virtual reality experiments - Screen-based setup and HMD system); Surveys	14 participants	Presence Questionnaire (PQ) scores.	Scenario condition; Vehicle speed; Vehicles density.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Feng *et al.* (2021)	Literature review	-	-	Data collection methods for studying pedestrian behaviour.
Granié *et al.* (2014)	Surveys/Controlled experiments	77 participants	Crossing decision; and Perception of pleasantness and safety.	Road environment; Type of buildings; Presence and type of sidewalks; and Presence of marked parking spaces.
Guth *et al.* (2005)	Controlled experiments (Semi-controlled naturalistic experiments)	26 participants	Safety margin; Gap detection latency; Percentage of crossable gaps; and Driver yielding behaviour.	Sight impairment and pedestrian mobility devices.
Habibovic and Davidsson (2012)	Accident data	56 observations	Critical event categories.	Weather; Light conditions; Speed limit; Intersection type; VRU facility; Pedestrian age; Pedestrian sex; Communication; Maintenance; Experience/knowledge; Organization; Road design; Vehicle design; and Injury severity.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
Haleem *et al.* (2015)	Accident data and Traffic volume counts	7630 observations	Injury severity.	Pedestrian age; At-fault user; Location; Hour; Presence of pedestrian signals; Presence of pedestrian refuge area; Light conditions; Weather; Vehicle type; Speed limit; Average annual daily traffic (AADT); Percentage of trucks; Crosswalk type; Road surface condition; Land use; and Pedestrian manoeuvre.
Hamed (2001)	Field observations (Unobtrusive observations) and Surveys (Face-to-face interviews)	400 observations (350 interviews)	Pedestrian waiting time and the frequency of attempts to cross.	Traffic volume; Vehicle speed; Walking origin and destination; Time of day; Pedestrian demographics; Type of vehicle; Involvement or witness an accident; Dimension of the group of pedestrians; and Vehicle time headway.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Hine (1996)	Surveys (Face-to-face interviews)	21 participants	Strategy and perceptions of safety and risk and Pedestrian perceptions of traffic flow.	Traffic flow conditions; Pedestrian age; health condition; and Mobility condition; Route choice; and Parked cars.
Holland and Hill (2007)	Surveys (Questionnaires)	293 participants	Intention to cross; Perception of risk; and Perceived value of crossing.	Pedestrian age; Pedestrian sex; and Driver status
Hu and Cicchino (2018)	Accident data	-	Number of fatalities.	Pedestrian age; Pedestrian sex; Road class; Land use; Location; Light condition; Blood alcohol concentration; Vehicle type; and Vehicle power-to-weight ratio.
Ishaque and Noland (2008)	Literature review	-	-	Pedestrian age; Pedestrian sex; Delay; Crossing types; Gap acceptance; Pedestrian compliance; Free flow speeds; and Speed-flow-density relationship.
Ismail *et al.* (2009)	Field observations (Video recordings); Methodological paper	2100 observations	TTC; DST; TG; and PET.	-

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Johansson *et al*. (2004)	Field observations (Video recordings)	3775 observations	Waiting times; Head movements; and Yield behaviour.	Pedestrian age.
Johnsson, Laureshyn, *et al*. (2018)	Literature review	-	-	Surrogate safety indicators.
Kong and Yang (2010)	Accident data	-	Number of fatalities.	Pedestrian age and Impact speed.
Kraidi and Evdorides (2020)	Accident data and Traffic volume counts	330 observations	Crashes frequency.	AADT; Traffic mean speed; Speed variation; Pedestrian crossing violations; Number of bus stoppings; Pedestrian walking along volume; Pedestrian crossing volume; Percentage of heavy vehicle traffic; Intersecting traffic volume; Number of intersecting side roads; Lane width; Median type; Pedestrian crossing facility; Roadside parking; and Number of parking, un-parking, and boarding events.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
LaScala *et al.* (2000)	Accident and Census data	1227 observations	Injury severity.	Pedestrian demographics (Sex; Age; Marital status; Education; Income; and Unemployment); Traffic flow; Characteristics of the roadway systems; Population density; and Alcohol availability
Lassarre *et al.* (2012)	Field observations (GPS instruments)	83 observations	Number of primary crossings; Number of secondary crossing; Distribution of primary crossings in relation to the distance from origin; Distribution of the type of crossing option; and distribution of the type of crossing locations.	Network characteristics; Road characteristics; Traffic lights location; Crosswalks location; Trip Length; and Traffic volume.
Lassarre *et al.* (2007)	Methodological paper	-	Number of primary crossings; Number of secondary crossing; Distribution of primary crossings in relation to the distance from origin; Distribution of the type of crossing option; and distribution of the type of crossing locations.	Network characteristics; Road characteristics; Traffic lights location; Crosswalks location; and Presence of sidewalks.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Leden (2002)	Accident data	66 observations	Accidents between left-turning vehicles and pedestrians and Accidents between right-turning vehicles and pedestrians.	Motorized traffic and Pedestrian flows.
Lin *et al*. (2015)	Existent databases constructed from Field observations (Video recordings) and Surveys (Questionnaires)	-	Driver compliant behaviours;	Intersection characteristics (Lane configuration; Pedestrian feature type; and Pedestrian feature location); Environmental conditions (Roadway condition; Weather; and Light conditions); Pedestrian presence; Dimension of pedestrians' group; Pedestrian location; Traffic signal; and Driver information (Age; Sex; and Risk and distraction).
Liu and Tung (2014)	Surveys (Face-to-face interviews)/Controlled experiments	32 participants	Walking time; Decision time; Remaining time; TG; Safety margin; Confidence level; Walking strategy;	Pedestrian age; Pedestrian sex; Time gap; Time of day; and Vehicle speed.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
Lobjois and Cavallo (2009)	Controlled experiments (Virtual reality experiments - CAVE-based system)	78 participants	TG; Initiation time; Crossing time; Safety margin; Accepted and rejected crossings.	Pedestrian age; Pedestrian sex; and Vehicle speed.
Lobjois and Cavallo (2007)	Controlled experiments (Virtual reality experiments - CAVE-based system)	78 participants	Crossing time; Response time; Distance gap; TG; Safety margin; Accepted and rejected crossings.	Pedestrian age; Pedestrian sex; Time constraint; and Vehicle speed.
Meir *et al.* (2015)	Controlled experiments (Virtual reality experiments - CAVE-based system)	24 participants	Crossing decision.	Scenario condition; Presence of zebra crossing; Presence of moving vehicles; and Field of view.
Morrongiello *et al.* (2015)	Controlled experiments (Virtual reality experiments - HMD system)	95 participants	Evasive action and Walking speed estimation.	Walking speed and Traffic condition.
Moyano Díaz (2002)	Surveys (Questionnaires)	146 participants	Violations; Errors; and Lapses.	Pedestrian age; Pedestrian sex; User status; and Accident involvement.
Olszewski *et al.* (2016)	Field observations (Video recordings) and Surveys (Questionnaires)	-	Danger indicator.	Minimum pedestrian-vehicle distance; Vehicle speed at the minimum pedestrian-vehicle distance; Pedestrian speed at the minimum pedestrian-vehicle distance; and Type of encounter.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Olszewski *et al.* (2019)	Accident data	-	Number of fatalities.	Area type (Urban or Non-urban); Location; Junction type; Road type; and Light conditions.
Olszewski *et al.* (2015)	Accident data	18850 observations	Number of fatalities.	Time of year; Area type; Road type; Road speed limit; Crosswalk location; Light condition; Pedestrian age; and Pedestrian sex.
Oxley *et al.* (2005)	Controlled experiments (Virtual reality experiments - Screen-based setup)	54 participants	Walking time; Decision time; Safety margins; Percentage of crossings; TG; Vehicle speed; and Distance gap.	Pedestrian age.
Papadimitriou *et al.* (2016b)	Field observations and Surveys (Questionnaires)	75 observations and participants	Pedestrians' declared and observed crossing behaviour.	Factors regarding: Pedestrians' demographics (Age and sex); Mobility and travel motivations; Attitudes, perceptions, and preferences; Self-assessment and identity; Behaviour, compliance and risk taking; and Opinion on drivers.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
Papadimitriou *et al.* (2016a)	Field observations (Video recordings) and Surveys (Questionnaires)	74 observations	Crossing choice.	Pedestrians' demographics; Mobility and travel motivations; Attitudes, perceptions, and preferences; Self-assessment and identity; Behaviour, compliance and risk taking; Opinion on drivers; Road type; Traffic flow; Traffic signals; and Presence of barriers.
(Papadimitriou *et al.*, 2017)	Surveys (Questionnaires)	75 participants	Clusters based on the results of questionnaires.	Pedestrians' demographics; Mobility and travel motivations; Attitudes, perceptions, and preferences; Self-assessment and identity; Behaviour, compliance and risk taking; and Opinion on drivers.
Papadimitriou *et al.* (2012)	-	-	Pedestrian exposure to risk based on: Mean pedestrian speed; Traffic volume; and Crossing probability.	Traffic volume; Walking speed; Traffic control; Lanes width; Number of lanes; Crossing location; and Pedestrian trip length.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Papadimitriou *et al.* (2009)	Literature review	-	-	Pedestrian movement and route choice models and Pedestrian crossing behaviour models.
Park and Ko (2020)	Accident data	24827 observations	Injury severity.	Pedestrian age; Pedestrian sex; Driver age; Driver sex; Vehicle type; Road characteristics; Land use characteristics; Population characteristics; Weather; Location; and Time variables.
Pešić *et al.* (2016)	Field observations (Unobtrusive observations)	1194 observations	Looking at the traffic before crossing the street; Waiting for the traffic to stop; Looking at the traffic while crossing the street; Starting the crossing of the street at the marked pedestrian crossing; and Finishing the crossing at the marked pedestrian crossing.	Pedestrian age; Pedestrian sex; Number of accompanying pedestrians; Manner of mobile phone use (Talking on the phone; Texting or viewing content on mobile phone; and Listening to music); and Location of the intersection.
Pugliese *et al.* (2020)	Controlled experiments (Virtual reality experiments - Screen-based setup)	81 participants	TTA and Speed estimation.	Pedestrian sex; Modality (auditory, visual, or visual and auditory); Vehicle speed; and Ambient sound condition.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Pulugurtha and Sambhara (2011)	Accident data	-	Crashes frequency.	Pedestrian volume; Traffic volume; Speed limit; Number of lanes; Presence of median; Number of transit stops; Land use characteristics; and Demographic and socio-economic characteristics of population.
Quistberg *et al.* (2015)	Accident and Census data	-	Crashes frequency.	Location type; Maximum posted speed; Average annual weighted daily traffic (AAWDT); Street width; Road classification; Street directions; Presence of bike lanes; Presence of truck lanes; Type of traffic control; Presence of crosswalk; Presence of median; Presence of turn lanes; Presence of bus lanes; Presence of parking lanes; Types of signals; Land use characteristics; Pedestrian age; Pedestrian sex; and Pedestrian ethnicity.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Rosén and Sander (2009)	Accident data	490 observations	Number of fatalities.	Pedestrian age and Impact speed.
Rosenbloom *et al.* (2008)	Field observations (Unobtrusive observations)	269 observations	Children’s crossing unsafe behaviours: not stopping at the curb; not looking before crossing; attempting to cross when a car is nearing; and running across the road.	Children accompaniment: child alone; child with an adult not holding the adult’s hand; and child holding the adult’s hand.
Schneemann and Gohl (2016)	Controlled experiments (Semi-controlled naturalistic experiments)	23 participants	TTZ; Distance-to-zebra (DTZ); and Relative brake actuation.	Speed limit; Vehicle speed; Maximum braking pressure; Vehicle speed at the time the driver uses the brake pedal; Vehicle speed at the time the pedestrian shows intention to cross; and Vehicle speed at the time the pedestrian starts to cross.
Schwebel *et al.* (2008)	Controlled experiments (Semi-controlled naturalistic experiments and Virtual reality experiments - Screen-based setup) and Surveys (Questionnaires)	176 participants	TG; Waiting time; Collisions; Tight fits; Starting delay; Simulator realism; Simulator sickness; and Temperament measures.	Pedestrian age.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Schwebel *et al.* (2012)	Controlled experiments (Virtual reality experiments - Screen-based setup); Surveys (Questionnaires)	138 participants	Time left to spare (Safety margin); Look left and right; Look away; Hits (Collisions); and Missed opportunities.	Pedestrian age; Pedestrian sex; Ethnicity; Walking experience; Media use; and Distracting condition.
Shankar *et al.* (2003)	Accident data	440 observations	Crashes frequency.	Number of lanes; Signal spacing; Centre turn lane corridors; Illuminated corridors; Corridors with mid-block/non-intersection crosswalks; Corridors with median treatments; and AADT.
Simpson *et al.* (2003)	Controlled experiments (Virtual reality experiments - HMD system)	24 participants	TG; Collisions; Tight fits; Cautious crossings; Crossing time; Inter-vehicle distance; Vehicle speed; Rejected gaps; and Number of gaps.	Pedestrian age and Pedestrian sex.
Stipancic *et al.* (2020)	Accident data and Traffic volume counts	-	Injury severity.	Crosswalk length; Number of lanes; Road Width; Intersection legs; Presence of curb extension; Presence of raised median; Number of turn lanes; Permitted parking; Restricted parking; Commercial entrances; and Signalization phase.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Stoker *et al.* (2015)	Literature review	-	-	Types of pedestrians and Built environment.
Sucha *et al.* (2017)	Field observations (Video recordings and Unobtrusive observations); Surveys (Face-to-face interviews); and Accident data	1584 observations (473 interviews)	Subjective feeling of safety; Driver yielding behaviour; Conflict situations.	Car speed; Car density; Pedestrian density; Accidents; Waiting time; Crossing width; Time of the day; Car/pedestrian ratio; Average traffic speed; Pedestrian age; Pedestrian sex; Dimension of pedestrians' group; Driver-pedestrian communication; and Pedestrian actions.
Sueur *et al.* (2013)	Field observations (Unobtrusive observations)	560 observations	Time to take a decision; Estimation of the time needed to cross the road safely; Estimation of the crossing time which represents a risk.	City; Pedestrian age; and Pedestrian sex.
Sween *et al.* (2017)	Methodological paper	-	-	Simulator design; Virtual environment; Virtual reality headset; Motion tracking; Hardware components; and Software components.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Sze and Wong (2007)	Accident data	73746 observations	Injury severity.	Pedestrian age; Pedestrian sex; Injury location; Pedestrian location; Pedestrian action; Special circumstance; Pedestrian contributory; Day of week; Time of day; Speed limit; Presence of traffic aids; Presence of traffic congestion; Presence of obstruction; Presence of junction control; Road type; Number of lanes; Environmental contributory factors; and Pedestrian negligence.
Tay *et al.* (2011)	Accident data	48381 observations	Injury severity.	Driver sex; Driver age; Driving intoxication; Pedestrian sex; Pedestrian age; Pedestrian location; Road class; Road segment; Road width; Number of lanes; Vehicle type; Weather; Time of day; and Region.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Thomson *et al.* (2005)	Controlled experiments (Virtual reality experiments - Screen-based setup) and Surveys (Questionnaires)	129 participants	Crossing time; Estimated crossing time; Accepted gap size; Starting delay; Missed opportunities; Tight fits; and Conceptual score.	Group (Trained and Control); Pedestrian age; and Test phase.
Turner *et al.* (2006)	Field observations (Video recordings)	-	Motorist yielding compliance.	Crossing treatment type; Speed limit; Number of lanes; Presence of parking lane; Presence of bicycle lane; Presence of curb extension; Distance to nearest signal; Type of crosswalk marking; Pedestrian crossing volume; and Peak period vehicle volume.
Ukkusuri *et al.* (2012)	Accident and Census data	-	Accident severity.	Exposure variables (Population and Signalized intersections); Socio-demographic characteristics; Land use characteristics; Road class; Number of lanes; Road width; Number of legs; Number of subway stations; and Percentage of non-motorized users.

Authors (Year)	Data collection method	Sample size	Safety/Behavioural indicators	Analysed factors
Várhelyi (1998)	Field observations (Unobtrusive observations and Video recordings)	1480 observations	Speed profile of passenger cars; TTZ; and TA.	Distance of car to zebra crossing; Presence of pedestrians at zebra crossing; and Type of interaction between car and pedestrian.
Wogalter *et al.* (2001)	Surveys (Questionnaires)	380 participants	Interest about buying an electric vehicle; Interest about buying a hybrid vehicle; Potential danger of lack of emitted sound; and Importance of the sound emitted by a vehicle.	Pedestrian demographics.
Yannis *et al.* (2013)	Field observations (Video recordings)	243 observations	TG and Crossing probability.	Waiting time; Vehicle speed; Vehicle distance; Traffic gap; Lane; Pedestrian age; Pedestrian sex; Presence of illegal parking; Vehicle type; and Vehicle size.

Authors (Year)	**Data collection method**	**Sample size**	**Safety/Behavioural indicators**	**Analysed factors**
Zegeer *et al.* (2006)	Field observations (Video recordings); Accident data; and Surveys (Questionnaires)	4128 observations	Pedestrian intersection safety index (Ped ISI) based on: Perceived level of pedestrian safety; Motorist avoidance manoeuvres or conflicts; and Pedestrian avoidance manoeuvres or conflicts.	Traffic volume; Speed limit; Traffic control; Number of lanes; Number of right-turn traffic lanes; Number of left-turn traffic lanes; Crossing width; Median island width; Pedestrian signal; 85th percentile speed; Pedestrian signal; Crosswalk type; Land use.
Zhang *et al.* (2016)	Surveys (Questionnaires)	631 participants	Red-light running behaviour (run or not).	Pedestrian age; Pedestrian sex; Education level; Education level; Annual income; Trip purpose; Time requirement; Intersection familiarity; Tolerable waiting time; Time period in a day that running a red-light easier; Issues regarding signals, traffic, and road characteristics.
Zito *et al.* (2015)	Controlled experiments (Virtual reality experiments - CAVE-based system)	40 participants	Estimated speed; Visual attention and executive functions; Visuo-constructional abilities and abstract thinking; and Walking speed.	Pedestrian age and Vehicle speed.