Universidade do Minho
Escola de Engenharia

Leidy Marcela Barón Acela

The Influence of Social Interaction on Pedestrian Crossing Behavior in Urban Environments

February 2024

The Influence of Social Interaction on Pedestrian Crossing Behavior in Urban Environment

Leidy Marcela Barón Acela

UMinho | 2024

FCT Fundação para a Ciência e a Tecnologia

Universidade do Minho
Escola de Engenharia

Leidy Marcela Barón Acela

The Influence of Social Interaction on Pedestrian Crossing Behavior in Urban Environments

Doctoral Thesis
Doctoral Program in Civil Engineering

Work conducted under supervision of
Professor Doctor Elisabete Fraga de Freitas
Doctor Emanuel Augusto Freitas de Sousa

February 2024

ACKNOWLEDGEMENTS

This work was funded by Fundação para a Ciência e a Tecnologia (FCT) through the doctoral grant SFRH/BD/138728/2018. The completion of this research would not have been possible without the invaluable contributions of a remarkable group of individuals.

First and foremost, I would like to express my sincere gratitude to my supervisors, Professor Elisabete Freitas and Dr. Emanuel Sousa. Professor Elisabete Freitas, your exceptional guidance, unwavering support, and constant availability throughout my doctoral journey have been deeply appreciated. Your extensive expertise and willingness to share knowledge have played a pivotal role in shaping my understanding of the subject and fostering my professional development.

To Dr. Emanuel Sousa, I extend my heartfelt appreciation for your invaluable contributions to this work and your unwavering support, motivation, and guidance. Your profound knowledge and practical perspective have significantly enriched the quality of my research. Your expert insights and critical feedback have been instrumental in shaping the direction and depth of my doctoral project.

I also extend my appreciation to Professor Jorge Santos for his guidance in the initial stages of this project. His extensive knowledge and experience were crucial in establishing the foundation for this work.

To Professor Susana Faria, I am deeply thankful for your support during the data analysis phase of this research. Your expertise in statistics has been invaluable in ensuring the accuracy and robustness of the findings.

I want to express my deepest gratitude to my Colombian and Portuguese families. To my "nonitos", "papitos", and "chaparrita" in Colombia, and my husband, parents-in-law, brothers-in-law, and extended family in Portugal, I am incredibly fortunate to have your love, unwavering encouragement, and understanding throughout these years. Your belief in my abilities and consistent support have been a constant source of motivation, giving me the strength to overcome challenges and continue with this doctoral project.

I would also like to thank all my friends around the world, who have become more than friends—they are like family. In particular, Paula and Sandra have always been there for me despite the distance, offering unconditional support, finding ways to uplift my spirits, and even providing valuable medical advice. To those who are physically close and have helped make this journey more bearable, I thank you for your presence and friendship.

Finally, my sincere thanks go to everyone who participated in my research study and generously shared their time and knowledge. With their willingness to contribute, this thesis was possible. Their involvement has been instrumental in generating valuable data and meaningful insights.

Completing this doctoral thesis represents the culmination of years of hard work, dedication, and the support of numerous individuals who have shaped and influenced my academic career. I am genuinely grateful for their contributions and humbly acknowledge their impact on the development of this research.

Thank you all.

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.

RESUMO

Investigar o comportamento dos peões é essencial para melhorar os sistemas de transporte, aumentar a segurança, criar cidades acessíveis e promover o desenvolvimento urbano sustentável. Uma percentagem significativa de peões caminha em grupos sociais (amigos, famílias ou conhecidos que caminham juntos). As interações sociais têm um impacto profundo no comportamento individual, influenciado pelo contexto social e pelas ações dos outros. No entanto, existe pouca informação sobre a influência das interações sociais no comportamento dos peões durante o atravessamento de estradas em condições de baixa densidade pedonal. Este projeto de doutoramento tem como objetivo abordar as lacunas do conhecimento sobre como os indivíduos interagem em ambientes urbanos, investigando o comportamento dos peões em grupos sociais em comparação com indivíduos isolados, e analisando a influência de fatores sociais, externos e culturais na velocidade dos peões e na organização espacial dos grupos em diferentes fases do atravessamento da estrada. A tese consiste numa série de estudos que examinam os fatores referidos da interação social nos movimentos dos peões, utilizando observações empíricas e experiências semi-controladas. De forma geral, os resultados revelam que indivíduos isolados tendem a caminhar com uma velocidade maior do que grupos sociais, e grupos maiores apresentam velocidades de caminhada mais baixas. Trios têm distâncias maiores do que as duplas; grupos masculinos caminham mais rápido e mantêm distâncias maiores do que grupos femininos. Duplas caminham lado a lado, enquanto trios adotam uma formação em formato de "V". Os fatores externos com influência no comportamento dos peões, incluem as fases do atravessamento e as interações com veículos e outros peões. As velocidades, as distâncias e os ângulos dos peões mudam consoante as diferentes fases do atravessamento, e os fatores culturais também desempenham um papel significativo, com variações observadas nos padrões de movimento. Esses resultados destacam a importância de considerar os fatores sociais e culturais no projeto de infraestruturas e nas políticas amigáveis aos peões em diversos contextos urbanos. Os resultados obtidos com este projeto de doutoramento contribuem para aumentar o conhecimento do comportamento pedonal que pode ser utilizado para otimizar as instalações pedonais e desenvolver estratégias para aumentar a segurança rodoviária.

Palavras-chave: Comportamento Pedonal; Grupos Sociais; Comportamento de atravessamento; Fatores Culturais; Modelos Lineares Mistos

ABSTRACT

Studying pedestrian behavior is essential for improving transportation systems, enhancing safety, creating walkable cities, and promoting sustainable urban development. A significant percentage of pedestrians walk in social groups (friends, families, or acquaintances who walk together). Social interactions profoundly impact individual behavior, influenced by the social context and the actions of others. However, limited research exists on the influence of social interactions during road crossings under conditions of low pedestrian density.

This doctoral project aims to address knowledge gaps regarding how individuals move and interact in urban environments investigating pedestrian behavior in social groups compared to isolated individuals and analyzing the influence of social, external, and cultural factors on pedestrians' walking speed and the spatial organization of groups in different crossing phases.

The thesis consists of studies examining different aspects of social interaction in pedestrian movements using empirical observations and semi-controlled experiments. In general, findings reveal that isolated individuals tend to walk faster than social groups, with larger groups exhibiting decreased walking speeds. Triads have larger distances between individuals than dyads; male groups walk faster and maintain greater distances than female groups. Dyads walk side by side, while triads adopt a "V-like" formation. External factors influence pedestrian behavior, including crossing phases and interactions with vehicles and other pedestrians. The pedestrians' speeds, distance, and angles change according to the different crossing phases, and cultural factors also play a significant role, with variations observed in movement patterns and spatial organization. These findings emphasize the importance of considering social and cultural factors when designing pedestrian-friendly infrastructure and policies in various urban contexts.

The insights gained from this research contribute to enhancing pedestrian safety, optimizing pedestrian facilities, and developing strategies to reduce accidents. Policymakers and urban planners can use this knowledge of pedestrian behavior to make informed decisions, creating safer, more inclusive cities with sustainable transportation options.

Keywords: Pedestrian Behavior; Social Groups; Crossing Behavior; Cultural Factors; Linear Mixed Models

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

BMMs = Bayesian multilevel models

CO = Study site CO

EU = European Union

GLMMs = generalized linear mixed models

HCM = Highway Capacity Manual

ICC = intraclass correlation

IDEAM = *Instituto de Hidrología, Meteorología y Estudios Ambientales*

IPMA = *Instituto Português do Mar e da Atmosfera*

LMMs = linear mixed models

MMVs = micro-mobility vehicles

Num DF = degrees of freedom

PT = Study site PT

S1 = Study site S1

S2 = Study site S2

S3 = Study site S3

SD = Standard Deviation

SDGs = Sustainable Development Goals

SE = Standard Error

Sum Sq = Sum of Squares

UN = United Nations

VIF = Variance Inflation Factor

VPC = Variance Partition Coefficient

VRU = Vulnerable Road Users

WHO = World Head Organization

CHAPTER 1

INTRODUCTION

1.1. Motivation

The study of pedestrians' movement and behavior holds significant importance for safety mobility and comfort. Pedestrians play a crucial role in urban transportation systems, as walking is a fundamental mode of travel for many individuals (Delclòs-Alió et al., 2022). Knowing pedestrians' behavior, patterns, and needs is vital for designing inclusive and efficient transportation infrastructure (Yang et al., 2019). This objective aligns with the Sustainable Development Goal (SDG) 11 of the 2030 Agenda for Sustainable Development, which aims to create sustainable cities and communities by ensuring safe, inclusive, and sustainable transportation systems (United Nations, 2015).

Historically, cities have predominantly focused on prioritizing vehicular traffic, often overlooking the significance of human-centric active mobility and the detrimental environmental impact of motorized transport (Fonseca et al., 2020). Urban mobility alone accounts for a substantial portion of CO2 emissions and other pollutants from road transport (Nanaki et al., 2017). Notably, within the European Union (EU), around 30% of car trips cover distances less than 3 km, and 50% are shorter than 5 km (Hooftman et al., 2018).

In contrast, walking is an eco-friendly transportation option that promotes physical well-being, aligning with SDG 3 – Good Health and Well-being (Baker et al., 2021; United Nations, 2015). Consequently, walking is now recognized as crucial in transportation and urban policies to foster sustainable development (Baker et al., 2021; Fonseca et al., 2020). By gaining insights into the factors influencing walking behaviors, such as accessibility, walkability, and the built environment, urban planners and policymakers can make informed decisions to enhance pedestrian-friendly infrastructure and encourage active mobility (Guo & Loo, 2013).

Furthermore, pedestrian safety remains a significant concern, as more than half of global road traffic deaths involve pedestrians, cyclists, and motorcyclists, who are often neglected in road traffic system design in many countries. Within these vulnerable road users (URU), pedestrians represent 23% of deaths among the different types of road users worldwide (WHO, 2018). Identifying pedestrian behavior and analyzing their movements and interactions with other modes of transportation can help identify potential risks and develop measures to mitigate pedestrian crashes, thus improving pedestrian safety (T. Fu et al., 2019). This objective aligns with the targets of SDG 3, which aim to reduce road traffic injuries and fatalities (United Nations, 2015).

Studying pedestrian behavior encompasses examining how people move and interact in urban environments. Pedestrian movements inherently exhibit greater complexity compared to motorized traffic (Papadimitriou et al., 2009). Unlike vehicular flow, pedestrians possess more autonomy in selecting paths and exhibit varying compliance with traffic regulations. They can adapt their behavior in response to external stimuli while walking, with slight bumping and nudging often being tolerable and not necessarily requiring complete avoidance (Blue & Adler, 2001; Ishaque & Noland, 2008; Weifeng et al., 2003; Xu & Duh, 2010).

Numerous studies have demonstrated the significant influence of social interactions on human behavior (Askarizad & Safari, 2020; Moussaïd et al., 2010; Pelé et al., 2017; H. Singh et al., 2009). In urban settings, social groups, such as friends or family, are integral to pedestrian flows (Moussaïd et al., 2010; H. Singh et al., 2009). The social context, actions of others, and existing social structures within a crowd play a crucial role in shaping individual behavior (Moussaïd et al., 2010; Pelé et al., 2017). However, these studies have primarily focused on social interactions in high-density environments, such as crowded sidewalks and evacuation processes (D'Orazio et al., 2014; Moussaïd et al., 2010; Xiao et al., 2022).

It is essential to recognize that the behavioral effects of social interactions can vary at different pedestrians densities (Moussaïd et al., 2010). Previous research has primarily examined social groups' behavior in environments without vehicle interactions, leaving a critical knowledge gap regarding the influence of social interactions on pedestrian behavior during road crossings (Federici et al., 2014; L. Fu et al., 2019; Moussaïd et al., 2010; H. Singh et al., 2009). The impact of social interactions on pedestrian behavior may vary in low-density pedestrian environments. Therefore, it is crucial to investigate how social interactions influence pedestrian dynamics, not only in crowded areas but also in contexts characterized by lower pedestrian densities. By exploring the effect of social interactions in different urban settings, a more comprehensive understanding of pedestrian behavior can be achieved.

In addition, cultural factors play a pivotal role in shaping pedestrian behavior, necessitating an analysis of their influence on pedestrian dynamics (Pan et al., 2006). Cultural norms, values, and beliefs influence individuals' responses to their environment, attitudes, risk perception, traffic enforcement, and spatial behavior (Matsumoto, 2007). These cultural factors exhibit variation between countries and impact pedestrian behavior differently (Bosina & Weidmann, 2017). Analyzing the influence of culture on pedestrian behavior is vital for developing effective road safety campaigns and interventions that consider the wide range of social norms (Nordfjærn et al., 2014). Additionally, in many countries, roads still lack separate lanes for cyclists or adequate crossings for pedestrians and allow motor vehicle speeds that are too high (WHO, 2018). By incorporating social and cultural factors into the study of pedestrian behavior at street crossings, researchers can contribute to the objectives of SDG 10 – reduced Inequalities by ensuring that road safety measures account for diverse social norms and promote equitable outcomes (United Nations, 2015).

Therefore, considering social factors in different urban contexts when studying pedestrian behavior, particularly during road crossings, is paramount to enhancing safety, promoting sustainable transportation, and creating more inclusive and walkable cities.

1.2. Objectives

Pedestrian behavior during road crossings is a complex phenomenon influenced by various factors, including individual characteristics, social interactions, external, and cultural factors. Understanding how pedestrians behave in social groups and their interactions with the environment and other pedestrians is essential for improving pedestrian safety, optimizing pedestrian facilities, and developing effective strategies to reduce accidents. In light of these considerations, this doctoral thesis aims to achieve the following objectives:

- Address the gaps in knowledge regarding pedestrian behavior in social groups during road crossings, particularly under low pedestrian density conditions.
- Explore pedestrian behavior and movement patterns, specifically focusing on the differences between walking in isolation and walking in social groups during road crossings.

Research Questions:

To achieve the objectives of this study, the following research questions will be addressed:

- How do pedestrians in social groups behave during road crossings under low pedestrian density?
- What is the influence of group size and sex composition on pedestrian movement patterns and dynamics during road crossings?
- How do variations in walking speed, distance, and angles between pedestrians change across different phases of road crossings?
- What is the impact of external factors on pedestrian behavior during road crossings?
- How do cultural factors shape pedestrian behavior and influence walking dynamics during road crossings?

By addressing these research questions, this doctoral thesis seeks to contribute to the understanding of pedestrian behavior and provide valuable insights for improving pedestrian safety, optimizing pedestrian facilities, and developing effective strategies for reducing pedestrian crashes.

1.3. Thesis structure

Chapter 1 serves as the introductory chapter, providing a comprehensive framework for the research conducted. It establishes the motivation and objectives of the study while offering a detailed overview of the thesis contents.

Chapter 2 focuses on the literature review, which explores the theoretical foundations of the central themes addressed in the thesis. The literature review is structured into three sections:

1. Factors influencing pedestrian behavior: In this section are examined the different factors that influence pedestrian behavior, encompassing personal factors, social interaction-related factors, situational factors, and cultural factors. By exploring these influences, a comprehensive understanding of the complexities involved in pedestrian behavior is established.

2. Data collection methods and analysis: This section offers an overview of the methods employed to collect and analyze data concerning pedestrian behavior.

3. General conclusions from the state-of-the-art review on pedestrian behavior: This section presents overarching conclusions derived from the comprehensive review of the current knowledge of pedestrian behavior. It highlights the essential findings and insights gained from analyzing existing research.

Chapter 3 presents the results of an observational study conducted in urban environments. Video recordings were utilized to collect data on pedestrian volumes in crosswalks and sidewalks across four study sections. The study analyzed the prevalence of different group sizes among pedestrians to identify the most common group sizes for further investigation. Determining typical group sizes was crucial in developing the experimental protocols outlined in Chapters 4 and 5.

Chapter 4 presents an initial approach to analyzing pedestrian behavior using semi-controlled experiments. The first objective of this chapter was to establish the experimental protocol, including data collection and analysis methods. Considering the potential influence of social interactions on pedestrian behavior and the limited research available on analyzing these differences during road crossings, the primary focus was to examine the operational parameters of individual pedestrians and pedestrians in social groups. Specifically, the parameters of interest were the speed of each pedestrian and the spatial organization within pedestrian groups, including interpersonal distance and angles between pairs of pedestrians. The analysis covered three distinct phases of pedestrian crossings: (i) before, (ii) during, and (iii) after crossing. To achieve this, semi-controlled experiments were conducted at three different pedestrian crossings in Guimarães.

In **Chapter 5**, an extension of the study presented in Chapter 4 is conducted, aiming to incorporate cultural factors into the pedestrian behavior analysis. In addition to social and external factors, the study explores the impact of culture by comparing data collected from one of the study sections in Guimarães, Portugal, with data obtained from additional semi-controlled experiments conducted using the same experimental protocol in Bucaramanga, Colombia. The analysis includes data from sixty participants, with thirty individuals derived from the sample discussed in Chapter 4 and an additional thirty participants. The parameters examined in this analysis remain consistent with the previous chapter, focusing on speed, interpersonal distance, and angles between pairs of pedestrians.

Chapter 6 serves as the concluding chapter of the thesis, presenting the general conclusions derived from the research work conducted. It highlights the significant findings and results obtained throughout the study. Additionally, this chapter provides suggestions for future research directions within the field of pedestrian behavior.

CHAPTER 2

STATE OF ART

Walking is a widely adopted mode of transportation that offers numerous benefits, such as improving public health, promoting sustainable mobility, and contributing to the economy (Baker et al., 2021; Cavill et al., 2008). However, pedestrians face significant risks and are among the most vulnerable road users, accounting for a substantial portion of road crashes worldwide (Sheykhfard et al., 2021). Consequently, characterizing pedestrian behavior in urban areas is critical to enhancing pedestrian safety and comfort (Papadimitriou et al., 2017). In that regard, road crossings have gathered considerable interest among researchers. Crosswalks are critical locations where pedestrian-vehicle interactions are frequent and potentially risky (Cambon de Lavalette et al., 2009; Liu & Tung, 2014; Sheykhfard et al., 2021).

Pedestrian flow dynamics is a complex phenomenon that involves a wide range of individual and social behaviors. Effectively modeling these dynamics poses challenges due to the heterogeneous nature of pedestrian groups and the multitude of external factors that must be accounted to predict pedestrian behavior accurately. These factors span various dimensions, including individual characteristics, group size, intergroup relationships, external and cultural influences (Arellana et al., 2020; Moussaïd et al., 2010; Papadimitriou et al., 2010).

Researchers have employed various methods to study pedestrian behavior and analyze measures of effectiveness. The technique employed in these studies depends on the specific level of behavior under investigation (Ishaque & Noland, 2008). Pedestrian behavior has been classified at three different levels (Hoogendoorn & Bovy, 2004):

1. Strategic level: This level involves decisions related to departure time choice;

2. Tactical level: At this level, researchers focus on activity scheduling, selection of activity areas, and route choices to reach those areas;

3. Operational level: The operational level centers around walking behavior.

Given the focus of this thesis on analyzing social interactions among pedestrians within a flow, this chapter presents a literature review that primarily concentrates on the operational level of pedestrian behavior. At this level, pedestrian behavior encompasses instantaneous decisions that influence walking characteristics, such as walking fast, walking slowly, stopping, and waiting, and determining when to cross a street. However, it is also important to acknowledge the significance of the other behavior levels such as strategic and tactical (Ishaque & Noland, 2008).

2.1. Factors influencing on pedestrian walking behavior

The literature review was divided into four groups to facilitate the comprehensive analysis of the factors influencing pedestrian behavior during their movements. While serving as a structured framework, it is essential to note that these factors are not isolated but interact and mutually influence each other, shaping pedestrians' behavior. The identified groups of factors include the personal characteristics of pedestrians, social interactions among pedestrians, external factors, and cultural influences (Figure 1). To explain the complex interplay of these factors is essential for designing and managing urban spaces that prioritize safety, efficiency and cater to the needs of pedestrians.

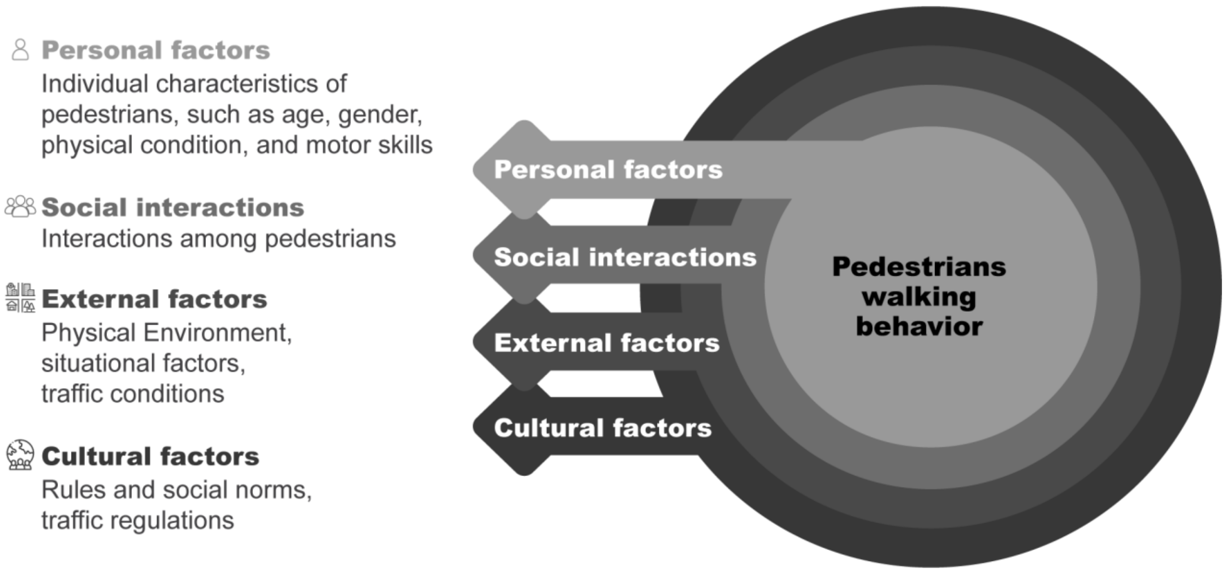


Figure 1. Factors with influence on pedestrian walking behavior.

According to Parisi et al. (2009), pedestrian dynamics can be broadly classified into two distinct behavioral states as a preliminary approximation:

- Normal state: Cooperative behavior characterized by an absence of pushing, with pedestrians stopping before physical contact.

- Competitive or panic state: Behavior marked by pushing, disregard for physical contact, or potential hurting others.

Considering the objectives of this research, the literature review will primarily focus on the factors that influence pedestrian behaviors in normal dynamics. In the subsequent sections, each group of factors will be examined in-depth, shedding light on their specific influences and implications for pedestrian behavior.

2.1.1. Personal factors

Personal factors play a significant role in influencing the choices and behaviors of pedestrians while moving. Several studies have highlighted the impact of individual characteristics, such as age, gender, physical condition, and motor skills, on pedestrian behavior.

These studies consistently demonstrate that walking speed declines with age (Liu & Tung, 2014; Willis et al., 2004). Moreover, Teknomo (2006) found that the presence of elderly pedestrians can reduce the average speed of the system at signalized pedestrian crossings, with a logarithmic relationship between the proportion of elderly pedestrians and the system speed. However, there is a saturation point beyond which the additional presence of slow pedestrians has minimal impact on the overall system.

Age-related declines in motor abilities, vision, and hearing, as highlighted by Dommes and Cavallo (2011), further affect pedestrian behavior, particularly in perceiving and reacting to traffic conditions. Consequently, older pedestrians may face increased challenges when crossing roads safely.

On the opposite direction, Pelé et al. (2017) showed that individuals between 20 and 30 years old are more prone to engaging in risky behavior by crossing against a red light, indicating a higher incidence of disregarding traffic signals among younger pedestrians. Also, Bernhoft and Carstensen (2008) indicate that a larger percentage of older pedestrians (66%) use formally marked pedestrian crossings compared to younger pedestrians (39%). This suggests that younger pedestrians tend to neglect the utilization of pedestrian infrastructure. However, it is important to acknowledge that while older pedestrians, as a group, generally tend to be more cautious and compliant with pedestrian infrastructure, there are exceptions, particularly among elderly individuals with poor health conditions. These individuals may deviate from the established principles of using existing infrastructure and choose to cross the road independently, even if it means avoiding detours.

Regarding sex, men typically exhibit a faster walking speed than women on average (Rajat et al., 2011; Willis et al., 2004). Studies have shown that men are more likely to cross the road against the "no walking" sign than women (Pelé et al., 2017; Rosenbloom et al., 2008; Yagil, 2000). Yagil (2000) found that men and women have different priorities when crossing the road, with men being more influenced by traffic volume and physical conditions, while women are more affected by the presence of others and their beliefs about others' behavior.

Additionally, Holland and Hill (2007), through a questionnaire evaluating the intention to cross and the perceived risk in hypothetical textual risk descriptions, concluded that women are less likely than men to attempt crossing under risky situations. Furthermore, Díaz (Díaz, 2002) analyzed attitudes towards (illegal) mid-block crossing and found that young individuals, especially males, have a more positive attitude towards committing violations as pedestrians compared to adults, reporting more violations, errors, and lapses.

It is important to note that individual characteristics alone do not wholly explain pedestrian behavior. Interactions among individuals within a group and with pedestrians from outside the group also play a significant role. Thus, the factors associated with behaviors resulting from social interactions among pedestrians will be explored.

2.1.2. Factors associated with social interactions between pedestrians

Social interactions significantly impact individual behavior, influenced by the social context and the actions of others (Askarizad & Safari, 2020; Moussaïd et al., 2010; H. Singh et al., 2009). Two areas of research investigate how others influence our actions. The first area, social facilitation, explores how the presence of others or co-acting with others affects our overall performance. The second area, ideomotor approaches, examines how observing others' actions triggers specific tendencies in us to engage in similar actions (Sebanz et al., 2003).

In addition, according to Nessler and Gilliland (2009), individuals can adapt their actions in response to cues from others, known as "interpersonal coordination." Interpersonal coordination refers to the relationship between individual and collective properties that emerge from interactions (Issartel et al., 2007). Interestingly, when two individuals walk together, they often synchronize their movements almost perfectly. A qualitative study by Zivotofsky and Hausdorff (2007) found a relatively high synchronization frequency between unfamiliar individuals, occurring in almost 50% of all tests.

Also, individual behaviors can be strongly influenced by social identities, peer pressure, or principles of social proof (Evans & Norman, 1998; Martin, 2006). It is widely accepted that individuals behave differently in a crowd compared to when they are alone or in a small group (Pan et al., 2006). Peer pressure, for example, can lead to behavioral changes among pedestrians moving within a group. For instance, at a signalized intersection, if a group of pedestrians sees some individuals crossing without permission, there is a possibility that those who initially waited for the green signal will follow the transgressing pedestrians' behavior (Martin, 2006). In situations with insufficient information, individuals are more likely to rely on the actions of others as a guide to determine their behavior. This phenomenon is known as social proof (Pan et al., 2006).

Understanding the impact of social interactions on pedestrian behavior is crucial in studying pedestrian dynamics, whether individuals are walking in a group or surrounded by others. The concept of a "group" in pedestrian behavior can be understood in two senses. In a sociological sense, a group refers to multiple pedestrians walking closely together, often exhibiting queueing behavior and moving as a cohesive unit. Additionally, there can be hierarchical social groups, such as families or friends walking together (H. Singh et al., 2009).

Pedestrians frequently engage in various social interactions while navigating urban spaces. They may need to maneuver to avoid or overtake each other to maintain their desired speed, or they may have to pause and wait to accommodate the movement of other pedestrians (Hussein & Sayed, 2015; Robin et al., 2009). Furthermore, pedestrians walking in social groups tend to adjust their speed and direction while maintaining interpersonal distances or following the movement of a group leader (H. Singh et al., 2009).

Robin et al. (2009) proposed a conceptual framework to characterize pedestrian behavior, depicted in Figure 2. The framework differentiates between unconstrained decisions made by pedestrians, which are influenced by subjective factors, and behavioral constraints induced by interactions with nearby individuals. Unconstrained decisions are affected by factors such as the individual's destination, the tendency to maintain the current direction, and unconstrained acceleration/deceleration based on the desired speed.

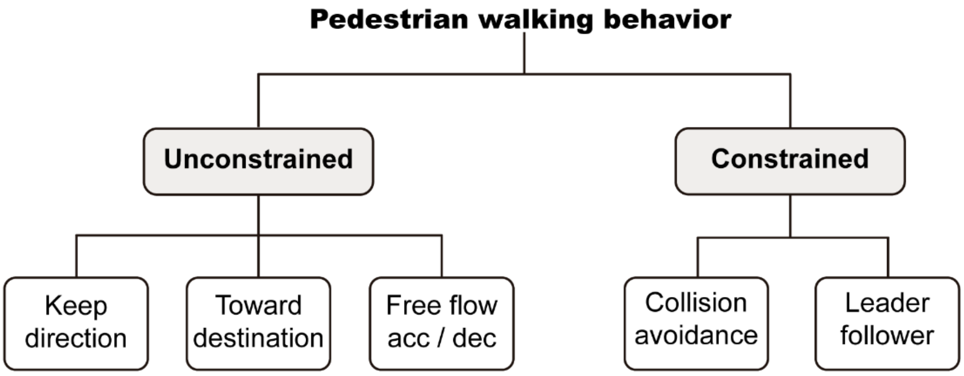


Figure 2. The conceptual framework for pedestrian walking behavior adapted from Robin et al. (2009).

In contrast, behavioral constraints are influenced by interactions with other individuals. The collision avoidance pattern captures the effects of potential collisions on the decision maker's current trajectory. On the other hand, the leader-follower pattern reflects the tendency of individuals to follow others in a crowd to benefit from the space created (Robin et al., 2009).

These factors, including unconstrained and constrained behavior influenced by the social context and walking within social groups, can be further analyzed in two categories: intra-group and inter-group interactions. Intra-group properties focus on the internal coordination among members of the same group, while inter-group properties involve the external interactions between individuals from different groups (Shao et al., 2014).

2.2.2.1. Intra-group interactions (social groups)

Intra-group interactions in pedestrian behavior encompass various aspects, including group size and the spatial organization of pedestrians within those groups.

Group size

Studies have shown that a significant portion of pedestrian flow consists of individuals intentionally walking together, such as friends or family members forming social groups of two or more people (Costa, 2010; Moussaïd et al., 2010; H. Singh et al., 2009).

Singh et al. (2009) conducted a study in Nottingham to quantify the sizes of groups in different locations, including shopping centers, train stations, and universities. The study aimed to investigate pedestrians' group dynamics and behavior in these settings. The results revealed that a substantial proportion of the crowd consisted of subgroups of two or more people. The proportion of size-2 groups was highest in commercial areas, while the university had a higher proportion of subgroups of three, and the train station had a higher proportion of subgroups of four or five. Generally, the size of subgroups ranged between two and four people (Figure 3).

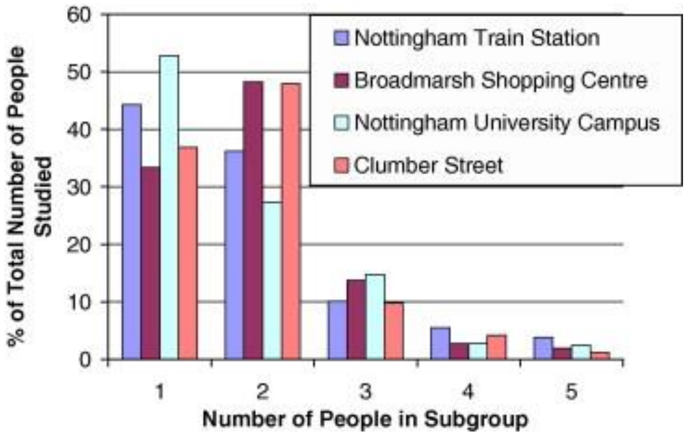


Figure 3. Sizes and proportions of social groups in different places (Singh et al. (2009)).

By comparing different populations, Moussaïd et al. (2010) found that the proportion of size-2 groups was higher in a commercial area with moderate density compared to a location with low-density conditions. This indicates that in commercial areas, where social interactions and group activities are more prevalent, people tend to move in groups with their friends.

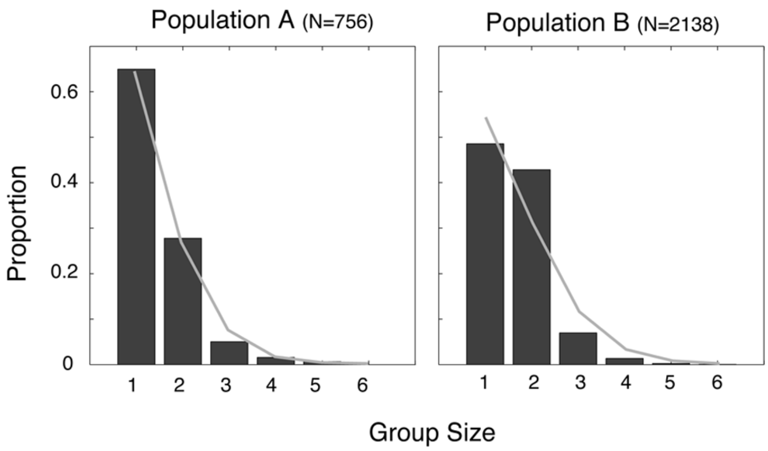


Figure 4. Sizes and proportions of social groups in different populations (Moussaïd et al., 2010).

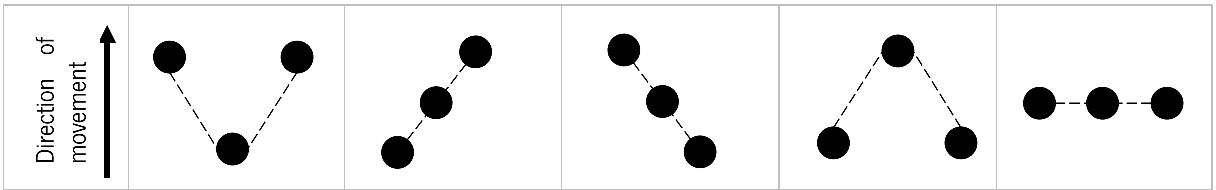
Another study by Federici et al. (2014) observed the movements of approximately two thousand people entering a university campus for an admission test. They found that the flow of pedestrians was predominantly composed of groups of two or more people (66%).

Spatial organization

The spatial organization of pedestrians within social groups is also an important factor associated with social interactions. How pedestrians in a group position themselves and maintain interpersonal distances can influence their collective behavior and navigation in urban spaces (Moussaïd et al., 2010).

The size of the group, composition, and affinity among group members can lead to different spatial arrangements (Costa, 2010; Moussaïd et al., 2010; H. Singh et al., 2009). Large groups, such as tourists, are more likely to split up rather than move side by side in a line (90°) (Costa, 2010). This division of groups can be attributed to factors like communication difficulties when members are far apart. It is hypothesized that individuals who do most of the talking, positioning themselves in the middle of the group while others listen, occupying the sides. This behavior is often referred to as "following the leader" (Moussaïd et al., 2010)

Costa (2010) identified four forms of spatial organization in groups of 2 and 3 pedestrians, as presented in Figure 5. The frequency of these spatial arrangements varied, with walking in v formation being the most common.



Frequency	40.4%	29.3%	16.2%	14.1%

Figure 5. Spatial arrangement of pedestrians groups according to Costa (2010).

Moussaïd et al. (2010) examined the spatial organization of groups of up to 4 people in locations with different pedestrian densities. At low densities, groups tended to walk side by side in a line perpendicular to the walking direction. As the density increased, groups adapted to the available space and formed a "V" shape with three pedestrians or a "U" shape with four members (Figure 6).

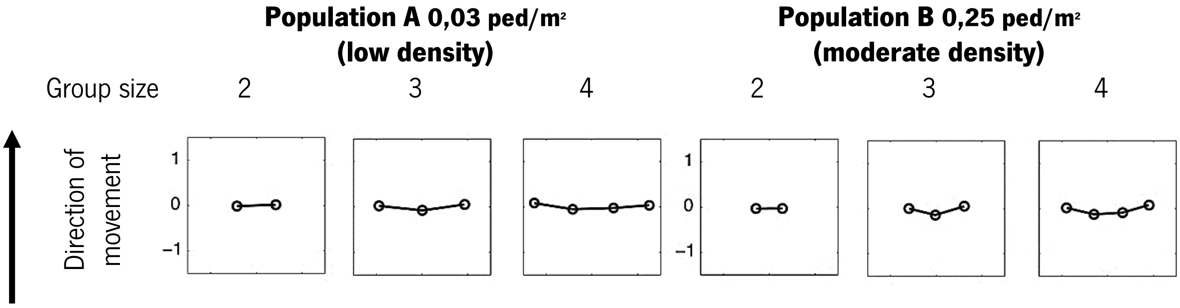


Figure 6. Spatial arrangement of pedestrians groups adapted from Moussaïd et al. (2010).

However, the efficiency of walking is considerably affected by the fact that "V" or "U" configurations are convex shapes (Figure 7 (b)), so it can happen that when the density reaches higher levels, safety prevails over social interactions, and group members choose to walk in river-like (Figure 8 (c)) (Karamouzas and Overmars, 2012).

(a) Line-abreast (b) V-like (c) River-like

Figure 7. Group formations according to Moussaïd et al. (2010) (adapted from Karamouzas and Overmars (2012)).

Lastly, other types of spatial organization were found in a study of the movements of approximately two thousand people at the University of Milano-Bicocca, as shown in Figure 8 (Federici et al., 2014).

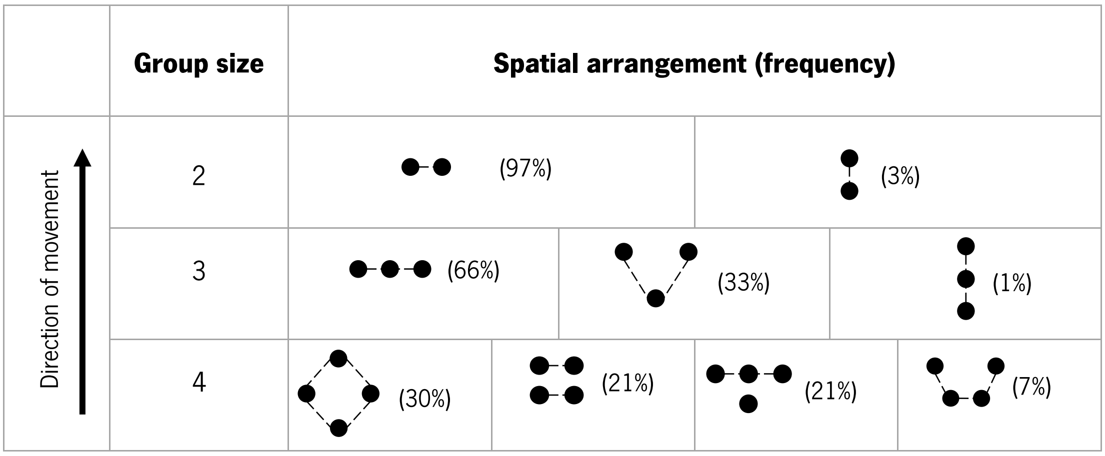


Figure 8. Spatial organization of groups of pedestrians, according to Federici et al. (2014).

A study by Costa (2010) examined the differences in interpersonal distances between pedestrians walking side by side based on gender. It was found that groups with male pedestrians walked more dispersed than groups with female or mixed groups. This behavior is attributed to male pedestrians' preference for avoiding intimacy with individuals of the same sex. However, this gender difference in proximity becomes less significant in larger groups, where interpersonal distances between men and women become more homogeneous.

Height differences among pedestrians can also influence walking behavior. When there is a noticeable difference in height within groups of two pedestrians of the same gender, they tend to walk less side by side than when their heights are similar. In mixed-gender groups, the person positioned in front is likelier to be a male pedestrian (Costa, 2010). Notably, the relationship between height and positioning within the group becomes less systematic when the height difference is significant, suggesting that reduced alignment can only partially be attributed to the taller person's speed.

Behaviors of social groups

Social interactions have been shown to affect pedestrians' behavior in various ways. Studies indicate that social groups, on average, tend to walk at slower speeds than individuals walking alone (Moussaïd et al., 2009; Willis et al., 2004). This decrease in speed is often attributed to factors such as distractions caused by a conversation among group members or the tendency to adjust the speed to match that of the slowest individual (Moussaïd et al., 2010).

Nessler and Gilliland (2009) suggest that individuals walking side by side with similar leg lengths tend to unconsciously synchronize their stepping, which can influence their walking speed.

Costa (2010) found that all-male groups exhibited higher average walking speeds compared to groups composed of women. Additionally, groups consisting of pairs with deeper reciprocal involvement tended to have slower speeds. This suggests that emotional connections within a group can influence walking speed, with stronger bonds leading to slower speeds.

According to research by Xu and Duh (Xu & Duh, 2010), bonded groups such as couples or families show a higher tolerance for shorter interpersonal distances than strangers. The study showed that the presence of bonding forces significantly impacts the redistribution of walking speeds among pedestrians, leading to deviations from the initially predicted speeds. This redistribution translates into delays and a phenomenon of overtaking among pedestrians, which have adverse effects on the dynamics of pedestrian evacuation. The study also indicated that cultural differences may influence the degree of interpersonal attachment, reflecting people's perspectives on independence and privacy.

Furthermore, social relationships within groups can also influence safety-related behaviors. Research by Pelé et al. (2017) showed that familiar individuals accompanying pedestrians could reduce the number of illegal crossings. This suggests that social relationships within groups can promote safer behaviors among pedestrians.

2.2.2.2. Inter-group interactions

Pedestrians are not only influenced by social interactions within the social groups but also by the social context and interactions with other pedestrians nearby, even if they are not personally known. Studies have shown that humans respond to social information derived from the behavior of others (Faria et al., 2010).

Faria et al. (2010) conducted a study that showed pedestrians are more likely to cross the road when their neighbors (unknown people) have already started crossing. However, this tendency is more prevalent among men than women. The study also suggested that social cues can encourage pedestrians to cross the road despite insufficient time to cross, leading to an increased risk of accidents.

Rosenbloom et al. (2008) and Pelé et al. (2017) observed that an increase in the number of pedestrians waiting to cross and an increase in the number of vehicles at the intersection are associated with a decreased chance of crossing at a red light. Thus, people who arrive alone at a crosswalk at a red light are likelier to break the traffic rules, possibly because they are not concerned about social criticism. In contrast, those surrounded by other pedestrians feel more committed to social order and norms.

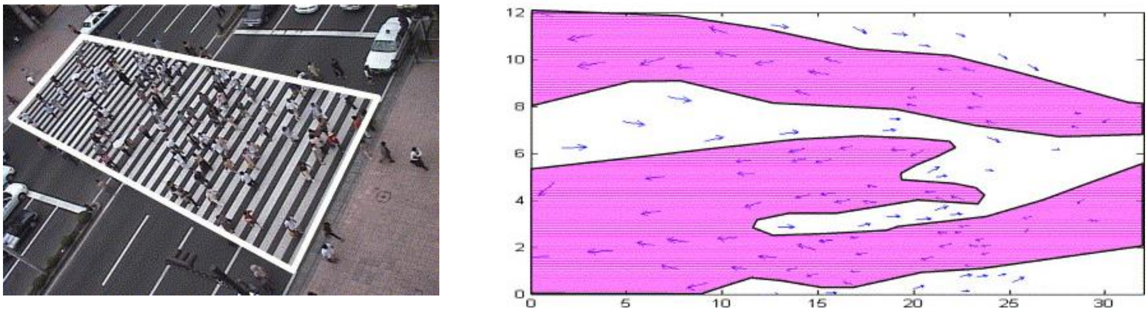
When different groups of pedestrians interact, conflicts and friction may arise. Through qualitative investigations, several social phenomena have been identified, including competitive behaviors and queuing behaviors (H. Singh et al., 2009; Teknomo, 2006).

Competitive behavior can arise in various situations where pedestrians naturally exhibit different walking velocities. Pedestrians with higher walking speeds often engage in overtaking behaviors to maintain their desired pace, especially when interacting with pedestrians moving at slower speeds. A typical example of such overtaking behavior can be observed during peak hours at railway stations, where pedestrians rush along the platform, maneuvering to avoid collisions while trying to catch their train (Yuen & Lee, 2012).

Moreover, at high densities of pedestrians, the presence of lanes with a uniform walking direction can lead to disruptions. Impatient pedestrians may attempt to overtake others by utilizing any available gap, which can obstruct the flow of pedestrians in the opposite direction. This competitive behavior can be mitigated by implementing measures to stabilize the lanes, such as incorporating physical barriers like trees or columns in the middle of the road. These barriers create a perception of a wall in the walking direction, discouraging pedestrians from attempting overtaking maneuvers and reducing disruptions to the flow of pedestrian traffic (Helbing et al., 2002).

On the other hand, queuing behavior involves self-organization into queues without causing obstructions. In dense crowds, pedestrians align themselves with others, forming collective behaviors instead of moving freely (Pan et al., 2006; Shao et al., 2014). In dense crowds, pedestrians have to align themselves (queueing behavior) with others to form collective behaviors instead of moving freely (Shao et al., 2014).

For example, when people cross the road in crosswalks with a higher proportion of pedestrians flowing in the opposite direction, they have less freedom to choose their speeds. Teknomo (2006) demonstrates in Figure 9, using a diagram of pedestrian speeds, the formation of lines in a high-density crosswalk.



(a) (b)

Figure 9. Queuing behavior (a) crossing for pedestrians (b) pedestrian speed diagram (adapted from Teknomo (2006)).

Pedestrians tend to follow the movement of others in the same direction, even if their speeds differ. The author's hypothesis justifies this self-organizing behavior arguing that pedestrians tend to reduce the effect of interaction, especially with a pedestrian moving in a different direction. The author also found that the most influential factors in queuing behavior are the total number of pedestrians (pedestrian volume) and the maximum acceleration.

Queuing behavior can be observed not only in high-density conditions but also under normal-density conditions when space is limited (Figure 10) (H. Singh et al., 2009).

Figure 10. Filmed evidence demonstrating the tendency of people to follow others from Singh et al. (2009).

Singh et al. (2009) also note that it is more likely for an individual to walk around a subgroup of people rather than through the middle of them (Figure 11 (a)). When a social group splits, and there are multiple obstacles to avoid, they will only regroup after all the obstacles have been avoided (Figure 11 (b)). In head-on encounters, pedestrians must choose whether to avoid the other person on the right or left side, significantly decreasing walking speed.

(a) Isolated pedestrian (b) Social group of 4 pedestrians

Figure 11. Actions taken during displacement, adapted from Singh et al. (2009).

2.1.3. External factors

Pedestrian behavior is influenced not only by personal and social dimensions but also by external factors associated with the environment in which pedestrians walk, such as the built environment and public space design (Feng et al., 2021; Rosenbloom, 2009; Willis et al., 2004). Pedestrians actively perceive and evaluate their environment, assess risks and opportunities, and adjust their behavior accordingly while walking on sidewalks or crossing roads (Papadimitriou et al., 2009).

Factors such as urban design, marked parking spaces, sidewalk width, and building function (e.g., presence and type of commercial activity) can impact pedestrians' perception of traffic density, attention to pedestrians, and the speed of vehicles, which in turn affect their decision to cross or not (Granié et al., 2014).

Preferred crossing environments include wide sidewalks, no parking, no markings, and a lively context with cafes and shops, as well as environments that provide organization and simplified use of public space through pedestrian crosswalks, well-defined sidewalks, unobstructed visibility, in a calm context with moderate traffic. These elements contribute to higher perceived comfort and safety (Granié et al., 2013).

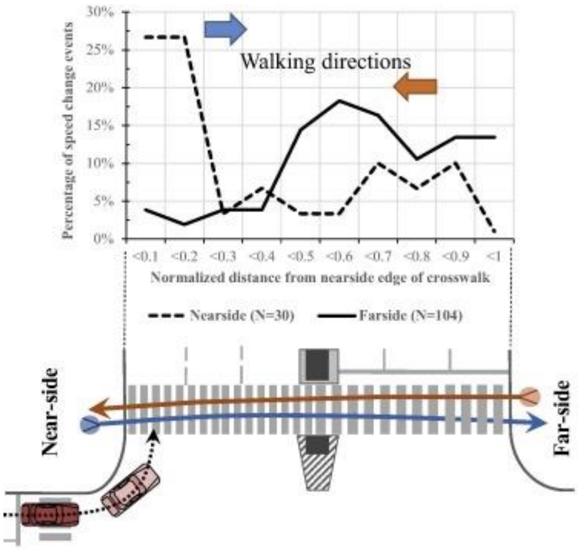
Different land use patterns generate varying numbers of trips, and an increase in the number of trips is associated with a higher probability of pedestrian casualties (Dissanayake et al., 2009). Studies conducted in Newcastle upon Tyne, England, have shown that pedestrian casualties are particularly associated with increased retail and community land use during working hours and retail land use, primarily clubs, and bars, outside working hours (Wedagama et al., 2006).

The interaction between pedestrians and vehicles is critical as it directly affects the likelihood and severity of accidents. Extensive research has been conducted to characterize pedestrian-vehicle interactions at unsignalized intersections, where many pedestrian crashes occur, and pedestrians are vulnerable to severe injury or death (T. Fu et al., 2019).

Factors such as the position and speed of approaching vehicles have been examined to explain pedestrians' crossing decisions (T. Fu et al., 2018; Soares et al., 2021). For example, pedestrians' crossing decisions are mainly based on their visual perception of the movement characteristics of approaching vehicles, particularly speed, and distance. Pedestrians tend to cross more frequently as distance increases, but crossing percentages are substantially lower at higher speeds (Soares et al., 2021).

According to Alhajyaseen and Iryo-Asano (2017), sudden pedestrian speed changes are important events that may significantly contribute to the severity of pedestrian–vehicle conflicts since drivers cannot easily anticipate them.

Pedestrians tend to accelerate when they are close to the conflict zone with motorized traffic, especially in the area where vehicles pass after making a turn. On the other hand, pedestrians on the opposite side accelerate in the middle of the crosswalk before entering the conflict area with traffic that changed direction (Figure 12 (a)). Deceleration events do not exhibit clear tendencies for near-side pedestrians. However, far-side pedestrians decelerate either when they start crossing or when they almost finished crossing (Figure 12 (b) (Alhajyaseen & Iryo-Asano, 2017).



Location of acceleration events Location of deceleration events

Figure 12. Example of the section under review, adapted from Alhajyaseen and Iryo-Asano (2017).

Along the same lines, Gorrini et al. (2018) found that the pedestrians walking speed crossing the road can be classified into three phases (Figure 13):

1. Approaching phase: The pedestrian travels on the sidewalk at a relatively stable speed.

2. Appraising phase: The pedestrian approaching the crosswalk decelerates to evaluate the distance and speed of oncoming vehicles (decision-making).

3. Crossing phase: The pedestrian decides to cross and speeds up. The crossing phase starts from the frame following the one with the lowest speed value before a long-term acceleration trend (Speed min).

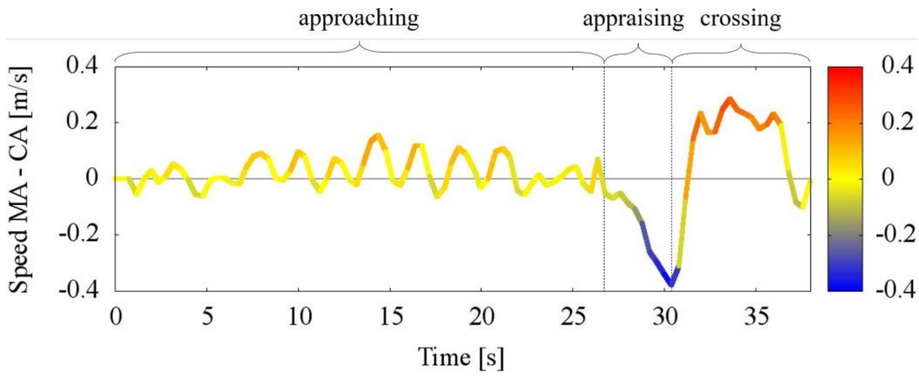
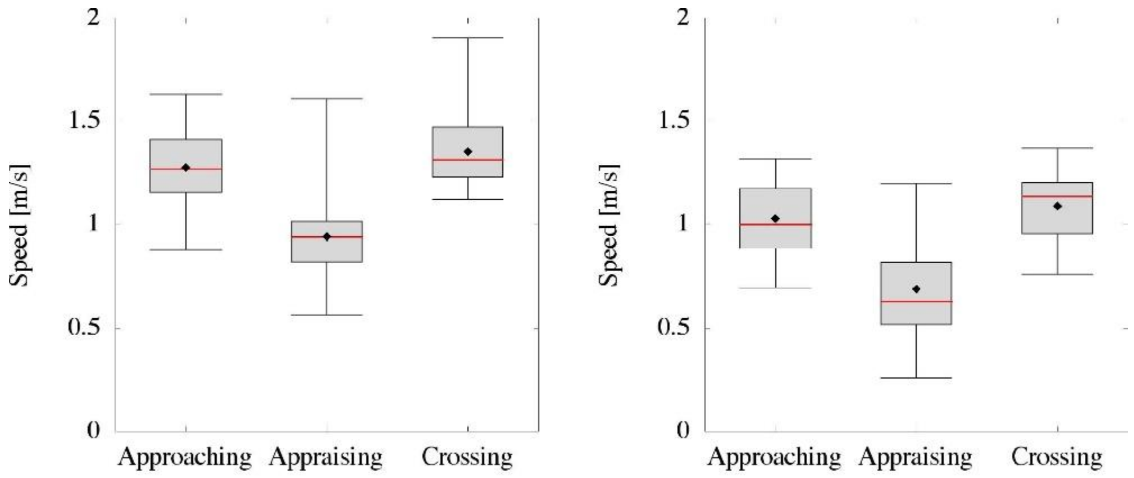


Figure 13. An exemplification of the trend analysis performed on the time series of speeds from Gorrini et al., 2018).

The results of (Gorrini et al., 2018) also showed that Ageing could impact crossing behavior in terms of motor skills decline, with elderlies walking slower and decelerating more during the appraisal phase (Gorrini et al., 2018).



(a) Adult Pedestrians (b) Elderly Pedestrians

Figure 14. The speed of adult and elderly pedestrians during the crossing phases from Gorrini et al. (2018).

Additionally, studies have indicated that pedestrian speeds are influenced by density level (Seyfried et al., 2005). People can walk faster in low-density areas than in higher-density areas (Figure 15) (Moussaïd et al., 2010). However, when pedestrian densities are very low, the presence of other pedestrians does not affect speeds, referred to as free-flow conditions and speeds in traffic engineering (Ishaque & Noland, 2008; Seyfried et al., 2005).

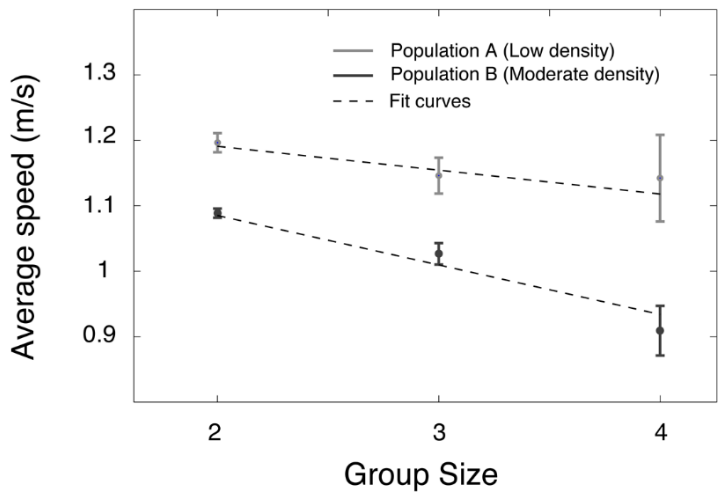


Figure 15. Effects of group size and density on pedestrian speed from Moussaïd et al. (2010).

According to Costa (2010), all these elements, such as density level, presence of obstacles, and the environment's geometry, can create difficulties in coordinating movements among group members, depending on the need to maintain spatial cohesion for communication during walking.

2.1.4. Cultural factors

The individual, social, and external factors explained before can also vary according to culture. Culture refers to the shared characteristics that influence how a group responds to its environment, including population density, climate, economic conditions, historical factors, and urbanization. Each cultural group develops specific rules, norms, and rituals to adapt to their ecological context, resulting in unique social norms that shape the structures and functioning of social institutions (Hofstede, 1980; Matsumoto, 2007; Pan et al., 2006).

Cultural factors influence the behavior of pedestrians; various studies have demonstrated significant disparities in risk perception across different countries. One notable investigation conducted in Norway and Ghana unveiled that Ghanaians, who encountered a more hazardous traffic environment, held a higher perception of the likelihood of being involved in traffic accidents than Norwegians. Furthermore, Ghanaians believed that the consequences of accidents would be more severe. The increased sensitivity to traffic risks among Ghanaians was attributed to factors such as a larger population, a growing number of cars, and a higher occurrence of accidents involving pedestrians or passengers. The issue of underreporting accidents in Ghana further complicated the accurate assessment of accident rates (Lund & Rundmo, 2009).

Additionally, Ghanaians displayed heightened sensitivity to various risks in general, potentially due to their exposure to poverty, diseases, and an underdeveloped healthcare system. In contrast, Norway's mass media, which emphasized health-related topics, influenced perceptions regarding the likelihood of sustaining injuries. The study also revealed a common trend among adolescents in both countries, where they exhibited a greater willingness to take risks in traffic and in general than adults. Notably, Norwegian males perceived risks as lower than females, whereas no significant gender differences were observed among Ghanaians. The study suggested that gender differences in risk perception might be less pronounced in developing countries than in high-income countries (Lund & Rundmo, 2009).

For instance, France has a higher illegal crossing rate than Japan (67% vs. 6.9%, respectively). Interestingly, there are fewer illegal crossings in both countries when pedestrians are close to others

(41.9% in France vs. 2.1% in Japan). The researchers explain these results by the mimetic effect and compliance with group pressure, particularly in collectivist societies like Japan, where individuals are more rule-abiding and more aware of others' opinions. The fear of being criticized by others is more influential than the fear of being fined (Pelé et al., 2017; Sueur et al., 2013).

In the same vein, Nordfjærn and Şimşekoğlu (2013) investigated the behavior of individuals from different socioeconomic urban neighborhoods in Turkey. They discovered that cultural factors indirectly influenced pedestrian behavior by impacting attitudes, explaining approximately 60% of the variance in attitudes. Safe attitudes were found to be strongly linked to lower levels of risk-taking behavior. Vertical collectivism, which emphasizes interrelation and respect for authority, was associated with reduced risk-taking pedestrian behavior. Conversely, horizontal collectivism, which emphasizes interpersonal interdependence with less emphasis on hierarchy, was associated with higher risk-taking behavior.

Road user education is a critical factor that varies significantly depending on cultural context. According to Uzondu et al. (2020), a country's traffic safety culture reflects its social norms, values, and beliefs, shaped by formal and informal rules. While authorities enforce formal rules which can change rapidly, informal rules develop over time through interactions between road users and their environment. Cultural factors can strongly impact road safety in low-middle-income countries, where traffic regulations are often less explicitly defined and enforcement is sparse (Nordfjærn et al., 2014).

For instance, a survey conducted by the National Road Safety Agency of Colombia revealed that pedestrians exhibited the highest level of ignorance regarding traffic regulations compared to motorcycle and vehicle drivers and cyclists (Agencia Nacional de Seguridad Vial, 2021). Similarly, a survey conducted by the District Mobility Secretariat in Bogota found that respondents provided four different answers with similar percentages when asked about the meaning of a "zebra crossing," indicating a lack of understanding. Furthermore, 43% of drivers believed they should only yield to pedestrians when there is a stop sign, highlighting the need for increased awareness regarding prioritizing pedestrians at marked crossings. The confusion surrounding the interpretation of a zebra crossing in Colombia may be partly attributed to changes in regulations regarding when it should be marked at road intersections and the introduction of new traffic signs (Secretaria Distrital de Movilidad, 2019).

The non-compliance of road users to traffic norms is caused by several factors (e.g., deliberate violation of norms, inattention, low visibility of signage), and it is undoubtedly one of the leading causes of accidents at intersections (Gorrini et al., 2018). At non-signalized zebra crossings, drivers' compliance with traffic laws is crucial to ensure the safety of pedestrians. These laws require drivers to slow down or stop near the zebra crossing to yield to pedestrians. This is particularly important because non-signalized crossings lack semaphore systems that regulate the alternating flow of traffic. The compliance of drivers with these laws helps to prevent accidents and ensure the smooth and safe movement of pedestrians across the road (T. Fu et al., 2018; Gorrini et al., 2018).

In addition to studies focused on the influence of cultural factors on the behavior of pedestrians at street crossings regarding compliance or non-compliance with traffic lights and traffic education, other studies have investigated differences in operational factors, such as walking speed and interpersonal distance.

In a seminal work, Hall (1966) discussed how people from different cultures differ in interpersonal distance preferences depending on social contexts: when approaching a stranger (social distance), an acquaintance (personal distance), or a close person (intimate distance). Hall's theory of cultural norms and spatial behavior has influenced the understanding of cultural differences in social distance preferences. He suggested that cultural norms are crucial in determining the appropriate distance between individuals during social interactions. He argued that what is considered intimate in one culture may be considered personal or social in another, and these cultural norms vary according to geographic location.

Hall (1966) classified cultures into two broad categories based on their preferences for interpersonal distance: contact and non-contact cultures. Contact cultures are those in which people use closer interpersonal distances and engage in more touching, while non-contact cultures exhibit opposite preferences and behaviors. According to Hall's classification, Southern European, Latin American, and Arabian countries are considered contact cultures, while North America, Northern Europe, and Asian populations are non-contact cultures.

Despite Hall's (1966) theory has been criticized for being based on anecdotal evidence. Still it has influenced research on cultural effects on human spatial behaviors (Sorokowska et al., 2017). Studies have shown differences in distance preferences between countries. Remland et al. (1995) found that the Irish and Scottish dyads stood closer together than the English, French, Italian, and Greek dyads. Sorokowska et al. (2017) found significant variability in the interpersonal distance for different social interactions in 42 countries, with a high correlation between personal and social distance and between intimate and personal distance. Argentina, Peru, and Bulgaria had the least interpersonal distance (less than 90 cm), while Saudi Arabia, Hungary, and Romania had the highest interpersonal distances (more than 120 cm).

Similarly, Bosina and Weidmann (2017) found differences in the walking speed of pedestrians according to the country they are from. Denmark had the highest average speed at 1.73 m/s, while Malta had the lowest speed at 0.53 m/s. However, the authors noted that it was impossible to directly link these speed differences to the properties of each country since factors such as climate variations were not known.

The study conducted by Chattaraj et al. (2009) examined the correlation between speed and density in pedestrian dynamics, focusing on the fundamental relationship associated with self-organization phenomena. The research revealed a significant knowledge gap in comprehending this relationship, even in simple systems like pedestrian streams in corridors. The findings indicated that the speed of Indian test subjects exhibited less dependency on density than their German counterparts. Interestingly, the study also demonstrated that the more unordered behavior observed among Indian participants was surprisingly more effective than the ordered behavior displayed by the German participants. These findings suggest potential differences in self-organization behavior, highlighting the need for further investigation and understanding.

In conclusion, pedestrian behavior can vary depending on the geographical location due to the presence of cultural differences. Therefore, it is crucial to consider this aspect when studying pedestrian dynamics and designing appropriate infrastructures in specific countries or regions. To gain insights into cultural differences, the literature recommends conducting investigations in different regions and comparing pedestrian flow parameters (Vanumu et al., 2017). Analyzing pedestrian behavior necessitates considering personal characteristics, social interactions, external factors, and cultural influences.

2.2. Data collection methods and analysis

Researching pedestrian behavior involves employing various data collection methods, such as field observations, controlled experiments, and semi-controlled studies.

Field observations are commonly used to gather pedestrian behavior data in realistic environments. This method entails manual counting, and the use of cameras or sensor systems like GPS, Wi-Fi, and Bluetooth to record pedestrian behavior (Feng et al., 2021).For instance, field observations have been employed to collect behavioral data about pedestrian groups' movement dynamics. Video recordings have been utilized to study the impact of group behavior on crowd dynamics, with a focus on the spatial movement behavior of social groups or interactions between pedestrians and interactions with vehicles (Hussein & Sayed, 2015; Moussaïd et al., 2010; H. Singh et al., 2009). Studies in this area have analyzed walking speed, interpersonal distance, step frequency, and walking patterns of pedestrians considering individual characteristics, group size, and sex.

Field observations have the advantage of capturing behavior in natural settings but have limited controllability, and obtaining permissions for data collection can be challenging (Feng et al., 2021). Data richness and quality are advantages, but accuracy may be influenced by sensor setup and techniques. Additionally, field observations are time-consuming, challenging to arrange, and require significant investment for data interpretation.

Contrarily, controlled experiments allow researchers to observe participants' movements and manipulate specific interest factors. They provide advantages in terms of controllability, data richness, and quality. However, they raise concerns regarding the validity and representativeness of results and the costs associated, for example, with creating artificial experimental environments. Also, while controlled experiments may be used to study specific factors their results may not be generalizable to different situations (Feng et al., 2021).

Many studies have used laboratory-controlled experiments to investigate pedestrian movement dynamics in various settings. A few have examined the impact of bottleneck width on pedestrian movement dynamics (Liao et al., 2014), while others have investigated pedestrian behavior in corridors (Moussaïd et al., 2009), intersections, and merging movements (Lian et al., 2017). Collision avoidance behavior has also been extensively researched, including studies on pedestrians avoiding obstacles (Wang et al., 2020) and strategies of social groups and individuals in multi-directional flows (Hu et al., 2020).

Semi-controlled studies bridge the gap between controlled experiments and observational studies. This type of study focuses on examining how behavior is influenced or changed when a specific task is added while keeping other factors constant and under control. For example, the researchers can assign participants to groups, select the route, and define the tasks, while participants can decide if, when, where, and how to perform them (Kircher et al., 2017).

For example, (Melnikov et al., 2022) conducted experiments to examine the effect of sun exposure on route choice in a tropical city. By conducting semi-controlled experiments, the researchers manipulated and controlled the variable of interest, the level of sun exposure, while observing and measuring the resulting pedestrian behavior. Participants were likely assigned to different groups or conditions where they experienced varying levels of sun exposure during their route choices.

Semi-controlled studies have some limitations and pose challenges, such as participants' awareness of being in a study and the restrictions imposed by the study design. Additionally, data analysis from semi-controlled studies can be complex and may require approaches unique to each study and research question (Kircher et al., 2017).

The complexity of pedestrian behavior also poses challenges for data analysis. In a field where pedestrians are independent entities, various studies have utilized statistical tests such as one-sided t-tests and ANOVA to analyze pedestrian behavior. For example, Moussaïd et al. (2010) employed a series of Student's t-tests to examine if the gait direction angle differed from 90° for groups of sizes 2, 3, and 4. ANOVA was also utilized to compare interpersonal distance in groups of different sizes (L. Fu et al., 2019), to assess significant differences in average speed based on factors like age, gender, and walking alone or in a group (Willis et al., 2004), and compare interpersonal distances and gait speed based on gender composition and group size (Costa, 2010).

However, in controlled and semi-controlled experiments involving a sample with dependent observations, repeated measures, and nested structured data, including repeated measures ANOVA sometimes is not a viable option. Linear mixed models (LMM)can address these issues, as they offer a more detailed and flexible approach than repeated measures ANOVA, particularly for longitudinal or complex pooled data. LMM allow handling missing data, skewed designs, identifying important relationships in the data, and accurate effect size estimates (Wainwright et al., 2007).

Previous studies on the behavior of pedestrians during street crossings have also shown the advantages of using linear mixed models for this type of study since they consider the inherent heterogeneity of observations made at different locations and differences in individual pedestrians (Aghabayk et al., 2021).

Few studies on pedestrian behavior have employed multilevel or hierarchical statistical models in field observations or controlled experiments. These models, which include frequentist or Bayesian frameworks such as linear mixed models (LMMs), generalized linear mixed models (GLMMs), and Bayesian multilevel models (BMMs), incorporate repeated observations from each participant. These models allow researchers to account for potential unobserved heterogeneity across different study sites and individual pedestrians (Aghabayk et al., 2021; Zhang & Fricker, 2021).

The choice of a statistical approach depends on various factors, including the research question, data characteristics, model complexity, and researcher familiarity with each framework (McNeish, 2016). Frequentist frameworks are suitable for scenarios where computational efficiency is crucial, simpler models suit, well-established normal distributions are applicable, or when researchers are more familiar with these methods. Bayesian frameworks are preferred for modeling complex relationships and temporal dependencies, incorporating prior knowledge, accommodating non-normal distributions, or handling complex random effects structures (McNeish, 2016; Smid et al., 2020; Zhang & Fricker, 2021).

2.3. Conclusion

Data collection methods for studying pedestrian behavior include field observations, controlled experiments, and semi-controlled studies, each with advantages and limitations regarding controllability, data richness, quality, and generalizability. While crossing situations in realistic settings are highly variable, obtaining statistically significant conclusions necessitates a substantial number of observations, making data collection and analysis time-consuming. However, capturing the individual characteristics of pedestrians using these methods can be challenging. One approach to address these challenges is to conduct semi-controlled experiments involving pedestrian participants who willingly record their experiences.

Understanding pedestrian behavior in urban areas is crucial for enhancing pedestrian safety and comfort, particularly at crosswalks where frequent interactions between pedestrians and vehicles pose potential risks. The literature review has established a framework for identifying factors that influence pedestrian behavior, categorizing them into four groups: personal characteristics of pedestrians, social interactions among pedestrians, external factors, and cultural influences. These factors are interconnected and mutually influence one another. It is necessary to study the influence of all these factors on pedestrians' behavior while crossing the street.

Pedestrian behavior can be characterized by analyzing the speed of individual pedestrians, distances between pedestrians, and spatial organization. Many studies have analyzed the effects of personal characteristics such as age, sex, physical condition, and motor skills on pedestrian behavior. Older pedestrians tend to walk more slowly, while younger pedestrians may engage in risky behavior. Men generally exhibit faster walking speeds and a higher likelihood of engaging in risky behavior than women.

Moreover, social interactions also influence pedestrian behavior, whether individuals are walking in a group or surrounded by others. Studies have demonstrated that a significant portion of pedestrian flow consists of intentional social groups, such as friends or family members walking together. Intra-group interactions, including group size and spatial organization of pedestrians within the group, shape pedestrian behavior. Different spatial arrangements are influenced by group size, composition, and affinity.

Additionally, social cues derived from the behavior of others significantly impact pedestrians' decisions, including whether to cross the road or adhere to traffic rules. The presence of other pedestrians and approaching vehicles at an intersection affects pedestrians' compliance with traffic rules. When surrounded by others, individuals are more likely to conform to social norms and less likely to break traffic regulations. However, no studies have specifically investigated the effects of social interactions on operational factors characterizing pedestrian behavior during street crossing, such as speed, distance, and spatial organization.

Infrastructure design, traffic conditions, and cultural norms also influence pedestrian behavior. Factors such as sidewalk width, land use patterns, and specific external features influence pedestrians' perception and decision-making. Density levels affect pedestrian speeds, with people generally walking faster in low-density areas than in higher-density areas. Difficulties coordinating movements among group members can arise due to elements such as density levels, obstacles, and the environment's geometry. Maintaining spatial cohesion for communication during walking can be challenging under such circumstances. An open question remains: How do social factors influence pedestrian behavior under low-density conditions, and do external factors also have an impact?

Cultural norms and social pressures significantly impact pedestrian behavior, with collectivist societies emphasizing rule adherence and individualistic societies prioritizing personal opinions. Cultural differences manifest in operational factors such as walking speed and interpersonal distance, with contact cultures exhibiting closer distances. Pedestrian walking speed varies across countries, potentially influenced by cultural factors and climate variations. Further investigation is required to understand the varying patterns of speed and spatial organization phenomena resulting from cultural differences in pedestrian behavior during road crossings.

Understanding the complex interplay of these factors is crucial for designing and managing urban spaces that prioritize pedestrian safety and efficiency. By considering personal characteristics, social interactions, external factors, and cultural influences collectively, improving pedestrian experiences and enhancing urban planning is possible.

CHAPTER 3

OBSERVATIONAL STUDY

3.1. Introduction

This chapter presents the results of an observational study focusing on the size of pedestrian groups, composed of families and friends, who share common goals and exhibit specific behaviors to stay together within the pedestrian flow (social groups). Previous research has indicated that a significant portion of pedestrian flow consists of groups of two or more individuals (Moussaïd et al., 2010; H. Singh et al., 2009). These findings have primarily been derived from studies conducted in densely populated cities and under conditions of high pedestrian flow.

In addition, land use has been widely recognized as the primary factor contributing to generating and attracting traffic. Researchers have consistently found that land use patterns significantly influence the overall level of traffic flow and factors such as speed and safety (Dissanayake et al., 2009).

Therefore, this observational study aimed to investigate the proportion of pedestrians walking in social groups in cities with lower population density and under normal conditions (i.e., non-emergency and non-mass events). To achieve this objective, pedestrian flow counts were conducted on four streets with different land uses, which allowed defining the composition of pedestrian groups across diverse urban environments: School zones, Mixed land use areas, and Residential areas in two cities, Guimarães and Braga in Portugal. The findings obtained from this study served as the foundation for defining the size of the social groups that were analyzed in the subsequent chapters of this thesis.

3.2. Materials and Methods

Data collection was conducted in four locations representing pedestrian traffic in three different types of situations: school environment (Nova de Santa Cruz street, Braga), work and commercial environment (São Gonçalo avenue and Landers avenue, Guimarães), and residential environment (*Dom António Bento Martins Júnior* street, Braga) (Figure 16).

(a) (b)

(c) (d)

Figure 16. Locations: (a) Nova de Santa Cruz street, Braga; (b) São Gonçalo avenue, Guimarães; (c) Londres avenue, Guimarães; and (d) Dom António Bento Martins Júnior street, Braga (Source: Google).

Observations were made using video recordings of 1-hour duration and manual counts. These video recordings were part of the AnPeB project (Analysis of pedestrians' behavior based on simulated urban environments and its incorporation in risk modeling), which aimed to describe the interaction between pedestrians and vehicles at unsignalized intersections in areas with high accident rates.

The distribution of the groups was analyzed separately: during road crossing at a signaled pedestrian crosswalk (Figure 17), and in their movements on the sidewalk (Figure 18).

Figure 17. Crossing the street with a signposted pedonal passage (São Gonçalo Avenue, Guimarães).

Figure 18. Walking on the sidewalk (Nova de Santa Cruz street, Braga).

3.3. Results

3.1.1. Pedestrian traffic count in the school zone

Rua Nova de Santa Cruz is located near the University of Minho's Gualtar campus in Braga (Figure 16 (a)). This street features a mixed land use, with the presence of the university, commercial establishments, and residential buildings. The results of the pedestrian traffic counts on this street corresponded to the behavior of pedestrian groups in a school environment, primarily in their movements on the sidewalks (Table 1).

Table 1 - Counting of groups of pedestrians on sidewalks in the school zone (Nova de Santa Cruz street, Braga).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	115	177	127	103	522	522	39%
2	64	76	59	31	230	460	34%
3	18	21	16	13	68	204	15%
4	8	9	3	4	24	96	7%
5	1	2	1	3	7	35	3%
6	0	1	0	0	0	0	0%
7	1	0	0	0	2	14	1%
8	0	0	1	0	1	8	1%
Total	207	286	207	154	854	1338	100%

At this location, higher tendency for people to walk in larger groups with friends or colleagues was expected, given the presence of an attraction point such as the university. This hypothesis can be verified with the data from Table 1, where 61% of the 1338 pedestrians studied during the recording period were observed to be moving in groups of 2 or more individuals. The size of these pedestrian groups often varies between 2, 3, and 4 people, but there is also a smaller proportion of larger groups, ranging from 5 to 8 people.

Table 2 - Counting of groups of pedestrians when crossing crossings in a school zone (Nova de Santa Cruz street, Braga).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	61	99	74	62	296	296	41%
2	34	43	34	19	130	260	36%
3	8	7	7	9	31	93	13%
4	3	4	1	2	10	40	5%
5	1	0	1	2	4	20	3%
6	0	1	0	0	1	6	1%
7	1	0	0	0	1	7	1%
8	0	0	1	0	1	8	1%
Total	108	154	118	94	474	730	100%

Of the 1338 pedestrians analyzed, 55% (730) crossed the street at the signaled pedestrian crosswalk. For this case, Table 2 shows that approximately 60% of them were moving in groups of 2 or more individuals, exhibiting a similar distribution to the movements on the sidewalk, where the most common group size also varied between 2, 3, and 4 people.

Based on Figure 19, the variations in the percentages of each size according to the area are relatively small.

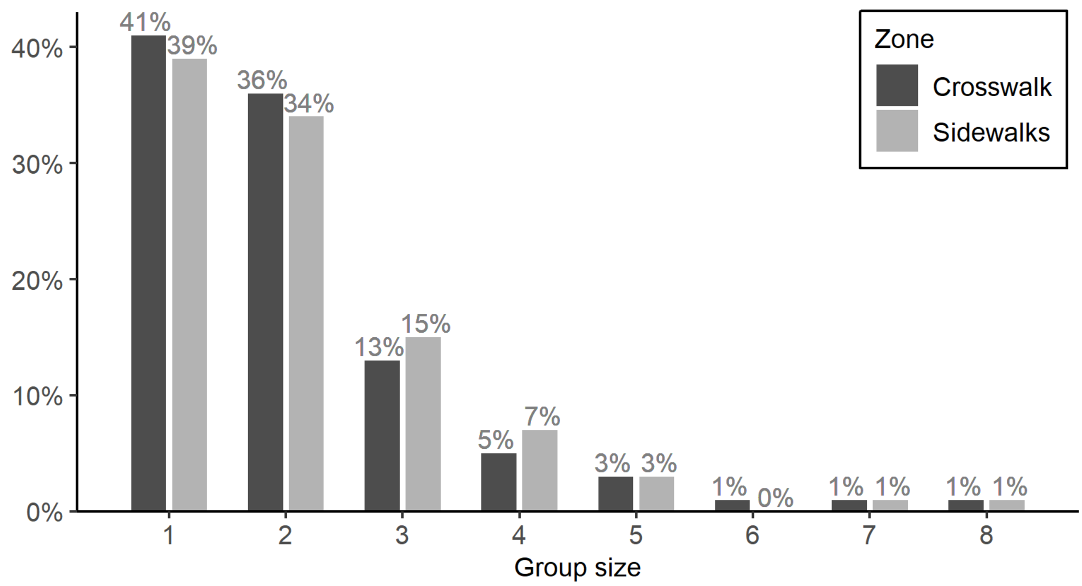


Figure 19. Comparison of the distribution of groups of pedestrians in a school zone, between walking on the sidewalk and crossing.

3.1.2. Pedestrian traffic count in mixed zone

To evaluate the impact of mixed land use areas, explicitly considering the presence of other attractions for pedestrian groups, a video recording from São Gonçalo avenue in Guimarães (Figure 16 (b)) was analyzed. This street exhibits mixed land use, with a shopping center, small commercial shops, and residential units. However, it is important to note that the results may have been influenced by the proximity of a school within a 100-meter radius and a bus stop in front of the shopping center.

Table 3 presents the results of pedestrian traffic counts obtained from the recorded videos, for the sidewalk movements. The distribution of pedestrian group sizes does not significantly differ from that observed in the school zone. As indicated, 42% of pedestrians were observed walking alone, while the remaining 58% of the 617 pedestrians captured during the recording period were part of groups ranging from 2 to 5 people.

Table 3 – Count of groups of pedestrians when traveling on sidewalks in an area with mixed land use (São Gonçalo avenue, Guimarães).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	35	73	90	64	262	262	42%
2	39	30	29	16	114	228	37%
3	16	5	9	3	33	99	16%
4	1	0	0	1	2	8	1%
5	3	0	0	1	4	20	3%
6	0	0	0	0	0	0	0%
7	0	0	0	0	0	0	0%
8	0	0	0	0	0	0	0%
Total	94	108	128	85	415	617	100%

Comparing this street with Nova de Santa Cruz street in Braga, the most notable difference is that the largest group size is 5 pedestrians, which is considerably smaller. Among the pedestrians analyzed in the video footage, 48% crossed the street at the pedestrian crosswalk (Table 4).

Table 4 – Counting groups of pedestrians when crossing crossings in an area with mixed land use (São Gonçalo avenue, Guimarães).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	37	40	40	38	155	155	53%
2	17	13	10	7	47	94	32%
3	7	1	1	3	12	36	12%
4	0	0	0	0	0	0	0%
5	1	0	0	1	2	10	3%
6	0	0	0	0	0	0	0%
7	0	0	0	0	0	0	0%
8	0	0	0	0	0	0	0%
Total	62	54	51	49	216	295	100%

However, in this case, the percentage distribution of pedestrian groups is different, with 47% of the crossing pedestrians moving in groups of 2, 3, and 5 people, while 53% of the studied pedestrians move alone.

As shown in Figure 20, the most notable difference is that the percentage of isolated pedestrians who cross the street through the crosswalk is higher than those who move along the sidewalk.

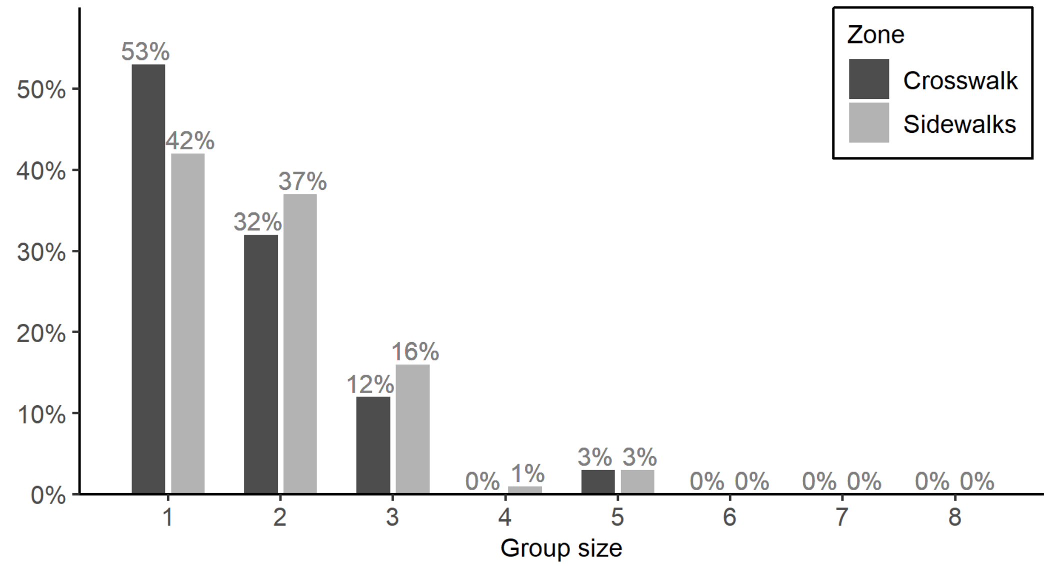


Figure 20. Comparison of the distribution of pedestrian groups between sidewalk travel and crossing, in an area with mixed land use.

Data from Londres avenue in Guimarães was also analyzed (Figure 16 (c)). This location features small commercial shops, bars, and cafes, making it a mixed land-use area. There is a shopping center and a hospital in its vicinity, but it is further away from a school zone. The results obtained from the pedestrian traffic count for movements on the sidewalks are presented in Table 5.

As can be seen from the analysis of the results (Table 5) of pedestrian movements observed on this street, 40% of people walk in groups ranging in size from 2 to 4 individuals. However, groups of 2 and 3 people account for 39% of the distribution by size, with only 1% corresponding to groups of 4 people.

Table 5 - Count of groups of pedestrians traveling on sidewalks in an area with mixed land use (Londres avenue, Guimarães).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	45	69	61	68	243	243	60%
2	10	14	23	21	68	136	34%
3	0	3	3	1	7	21	5%
4	0	1	0	0	1	4	1%
5	0	0	0	0	0	0	0%
6	0	0	0	0	0	0	0%
7	0	0	0	0	0	0	0%
8	0	0	0	0	0	0	0%
Total	55	87	87	90	319	404	100%

Out of the 404 pedestrians observed, 22% (90 pedestrians) crossed the street, and the pedestrian traffic count results are presented in Table 6. In this case, approximately 47% of pedestrians were moving in groups of up to 4 people, and the percentage of isolated pedestrians decreased by 7% compared to movements on the sidewalks (Figure 21).

Table 6 - Counting groups of pedestrians when crossing crossings in an area with mixed land use (Londres avenue, Guimarães).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	10	16	10	12	48	48	53%
2	3	5	4	4	16	32	36%
3	0	2	0	0	2	6	7%
4	0	1	0	0	1	4	4%
5	0	0	0	0	0	0	0%
6	0	0	0	0	0	0	0%
7	0	0	0	0	0	0	0%
8	0	0	0	0	0	0	0%
Total	13	24	14	16	67	90	100%

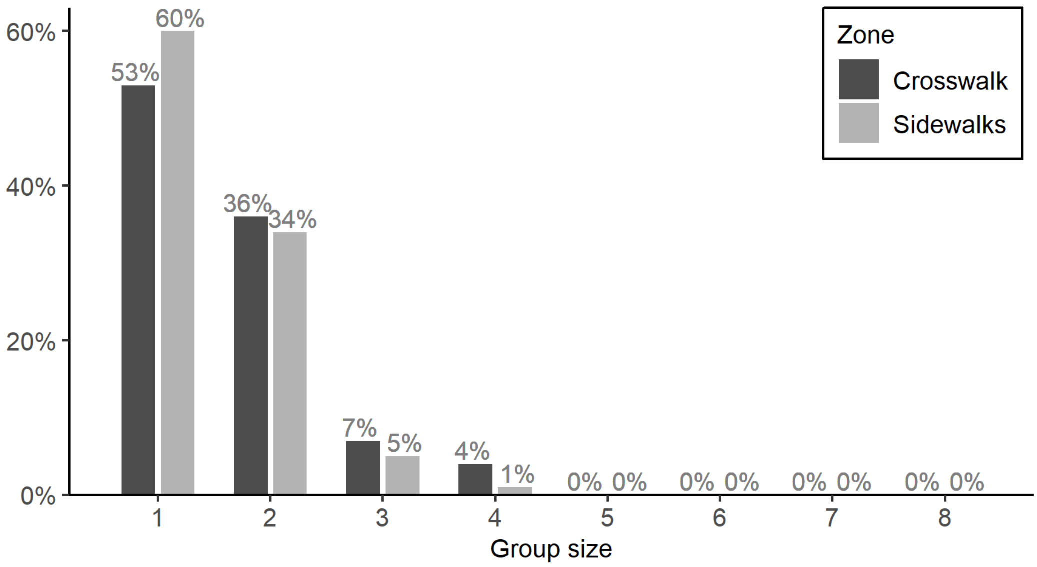


Figure 21. Comparison of the distribution of pedestrian groups between sidewalk travel and street crossing in an area with mixed land use.

3.1.3. Pedestrian traffic count in residential area

Finally, a video recording from Dom António Bento Martins Júnior street in Braga was analyzed (Figure 16 (d)), a street characterized by residential land use, with a predominant presence of residential buildings.

The results of the pedestrian traffic counts for movements on the sidewalks are presented in Table 7.

Table 7 - Counting of groups of pedestrians on sidewalks in a residential area (Dom António Bento Martins Júnior street, Braga).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	21	18	27	28	94	94	65%
2	5	5	1	2	13	26	18%
3	4	1	1	1	7	21	14%
4	0	1	0	0	1	4	3%
5	0	0	0	0	0	0	0%
6	0	0	0	0	0	0	0%
7	0	0	0	0	0	0	0%
8	0	0	0	0	0	0	0%
Total	30	25	29	31	115	145	100%

On the other hand, for pedestrian movements during street crossings, as seen from the analysis of Table 8 and Figure 22, there are no differences between the distribution of the size of pedestrian groups compared to the percentages for sidewalk movements. However, the percentage of isolated pedestrians decreased by 4%. In this case, 39% of the pedestrians studied (127 individuals) move in groups of between 2 and 4 people.

Table 8 - Counting of groups of pedestrians when crossing a residential area (Dom António Bento Martins Júnior street, Braga).

Nº people in the group	**Time interval (min)**				**Total groups**	**Total People**	**%**
	00 - 15	**15 - 30**	**30 - 45**	**45 - 60**			
1	21	16	20	20	77	77	61%
2	5	4	2	3	14	28	22%
3	4	1	1	0	6	18	14%
4	0	1	0	0	1	4	3%
5	0	0	0	0	0	0	0%
6	0	0	0	0	0	0	0%
7	0	0	0	0	0	0	0%
8	0	0	0	0	0	0	0%
Total	30	22	23	23	98	127	100%

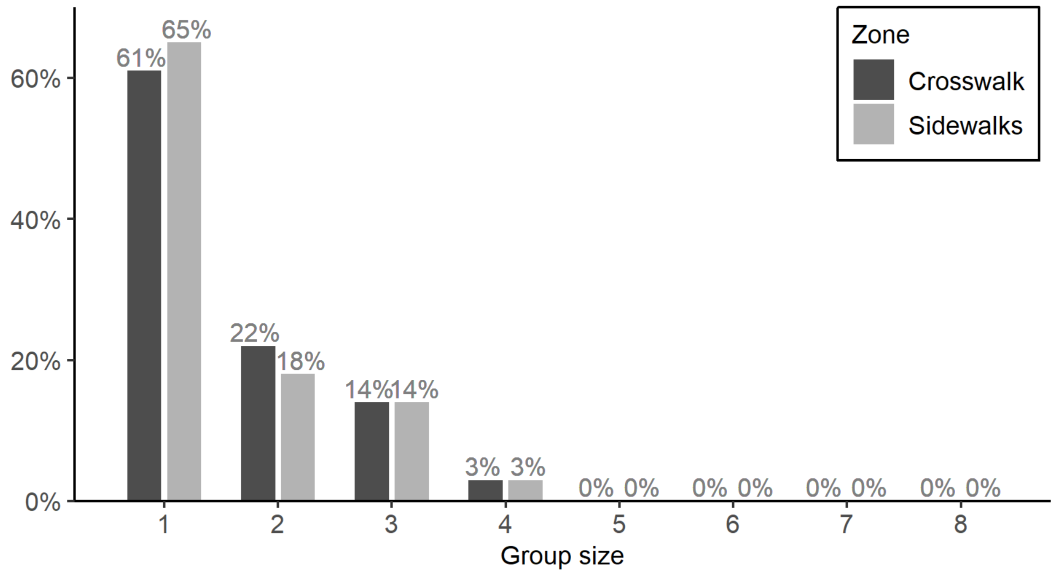


Figure 22. Comparison of the distribution of pedestrian groups between sidewalk travel and street crossing in a residential land use area.

3.4. Discussion and Conclusions

To compare the results of pedestrian traffic counts in the 4 locations with different land uses, representing pedestrians in 3 types of situations: academic environment, work and commercial environment, and residential environment, two graphs are presented showing the respective distributions of pedestrian group sizes during sidewalk movements and street crossings.

The results primarily show that a large proportion of the crowd consists of subgroups of two or three people, with the possibility of finding pedestrian groups of up to 8 people only in the school zone, where there are groups with a larger size.

For sidewalk movements, Figure 23 shows that the percentage of people in a group varies between 61% for a school environment, 58% for a commercial environment with a nearby school, 40% for a commercial/residential environment, and 35% for a residential environment. Groups of 5 people are rare in areas with a higher proportion of residential units.

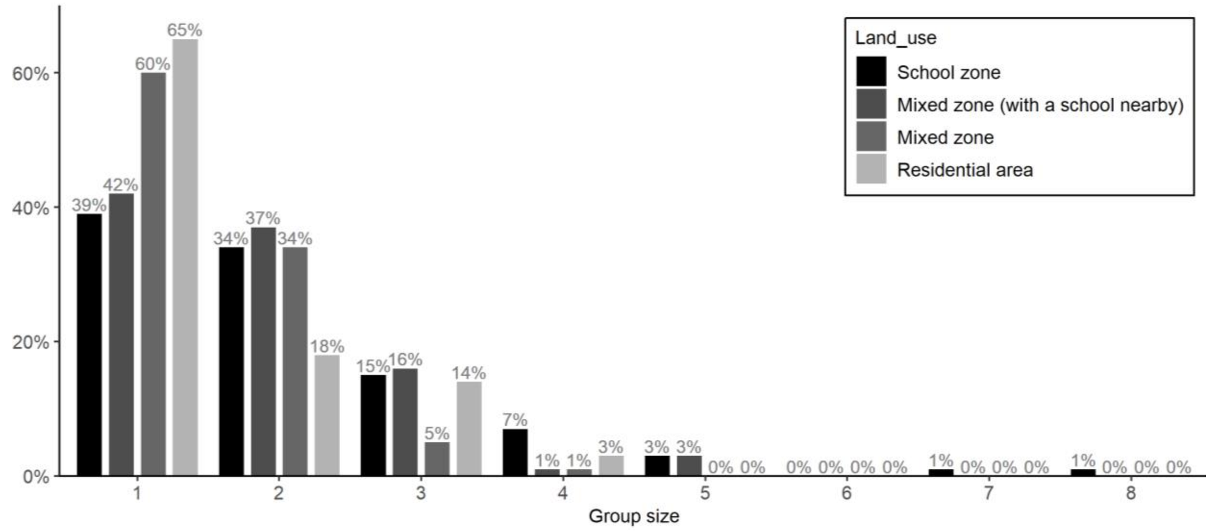


Figure 23. Distribution of pedestrian groups in sidewalk travel by dimension.

For street crossing movements, Figure 24 shows that the percentage of people in social groups varies between 59% for a school environment, 47% for a commercial environment with a nearby school, 47% for a commercial, and 39% for a residential environment. Similarly, to sidewalk movements in areas with a higher proportion of residential units, it is less likely for people to move in groups, while in commercial areas, more than 50% of pedestrians move in groups of 2 or more people.

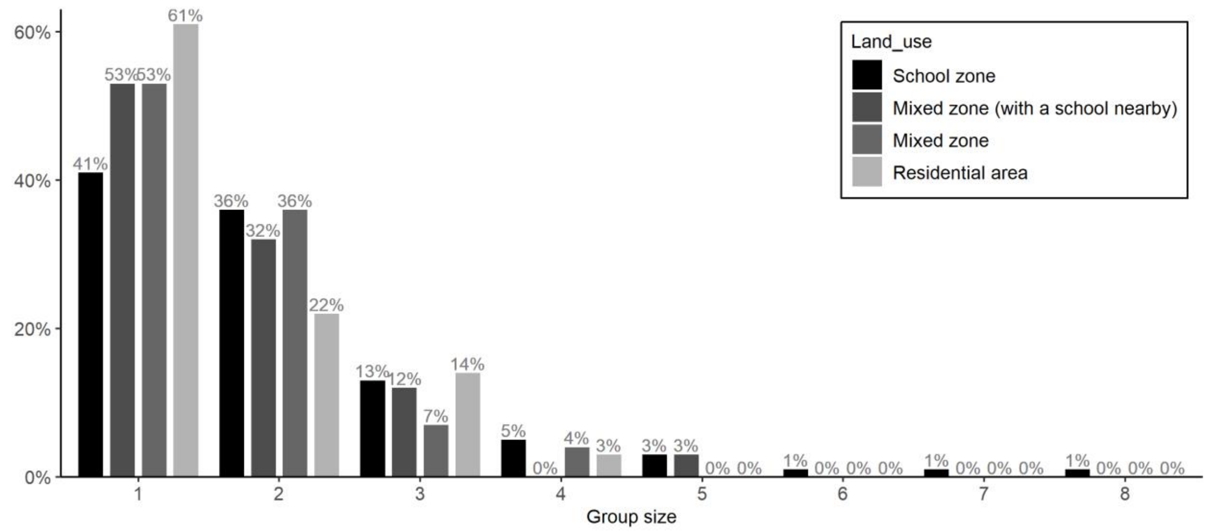


Figure 24. Distribution of pedestrian groups in street crossing by dimension.

Comparing the results of this observational study with the percentages of pedestrians walking in groups reported in previous research (Table 9) the findings of the mixed zone analyzed here aligns more closely with the findings of Moussaïd et al. (2010), they conducted part of his study in an public place that he characterized by low-density conditions, reporting a group walking percentage of 55%.

Table 9 – Previous results of percetage of pedestrians walking in group.

Description of the analysis area		**Percentage of pedestrians in group**	**Reference**
Shopping environment	Broadmarsh shopping center	67%	(H. Singh et al., 2009)
Shopping environment	Clumber Street	63%	
Travel environment	Nottingham train station	56%	
Work or study environment	Nottingham University	47%	
Low density conditions (public place in the city of Toulouse)	Population A	55%	(Moussaïd et al., 2010)
Moderate density conditions (crowded commercial walkway)	Population B	70%	

In contrast, the percentage of people walking in groups observed in a work or study environment differs from those reported by Singh et al. (2009), who reported the lowest percentage when compared with the shopping environment. It is important to consider that the streets analyzed by Singh et al. (2009) were located in areas that attracted a higher density of pedestrians. In this study, pedestrian counts were conducted in a mixed environment with residential and commercial areas, which could explain the discrepancies in the results.

Regarding the size of pedestrian groups, previous studies have indicated a significant percentage of pedestrians walking in groups of up to 4 people. However, the current study revealed that groups of up to 3 people were more common. This variation suggests that the composition of pedestrian groups may differ depending on the specific context and characteristics of the study area.

Furthermore, as mentioned earlier by Costa (2010), it was observed that larger groups tended to divide into subgroups of 2 and 3 people. This phenomenon indicates that even when pedestrians initially start in larger groups, they naturally form smaller groups or pairs as they navigate the urban environment.

These findings highlight the dynamic nature of pedestrian group sizes and the tendency for larger groups to disperse into smaller units during their movement. Understanding these patterns is crucial for designing pedestrian infrastructure and implementing appropriate measures to effectively accommodate groups of varying sizes.

Based on the abovementioned considerations, the study will proceed considering isolated pedestrians (1 person) and pedestrians in groups of sizes 2 and 3. By examining these specific group sizes, valuable insights can be gained regarding pedestrian behavior and their interactions within the urban environment.

CHAPTER 4

ANALYSIS OF PEDESTRIANS' ROAD CROSSING BEHAVIOR, IN SOCIAL GROUPS

4.1. Introduction

Social interaction plays a significant role in shaping the walking behavior of pedestrians, particularly on crosswalks or on sidewalks where they frequently have to adjust their path to accommodate others. Furthermore, pedestrians often walk in small social groups, comprising individuals with some kind of social connection, such as couples, friends, or families (Aveni, 1977; Coleman & James, 1961; Moussaïd et al., 2010; Yucel et al., 2019).

Previous studies have reported that the formations adopted by social groups and their walking speeds facilitate communication, although they may hinder the task of moving through a flow of pedestrians (Moussaïd et al., 2010; Rojas et al., 2016; Zanlungo et al., 2014). The behavior of social groups has been mainly analyzed in two scenarios: (i) In normal conditions (i.e., non-emergency and non-mass events), such as crowded commercial walkways or corridors connecting a train station with a shopping center (Do et al., 2016; Moussaïd et al., 2010; H. Singh et al., 2009; Zanlungo et al., 2019), and (ii) more complex scenarios, such as during evacuation processes or mass events (D'Orazio et al., 2014; Lu et al., 2017; Rutten et al., 2021; Xiao et al., 2022). In most of these studies, the observed difference between individuals and groups was related to the need of the latter ones to maintain cohesion, to facilitate social interactions and communication (Gorrini et al., 2014; Moussaïd et al., 2010).

Notably, the majority of them were conducted under medium to high population densities, and thus, the results obtained could have been explained mostly by the effort required for the groups to stay together. Importantly, to our knowledge, no study has specifically examined group behavior during road crossings, despite the prevalence of group walking and the critical importance of road crossing as a safety moment in everyday urban walking.

In this sense, this work intends to study the influence of size and sex composition on pedestrian behavior when walking in a group in urban areas in normal conditions with low pedestrian density and the difference in the pedestrian behaviors of the groups in three phases: before, during and after crossing the road. For this, semi-controlled experiences were carried out in three urban sites in Guimarães, with small groups of young pedestrians (1, 2, and 3) who had a defined path to walk, varying group size and sex composition.

Pedestrian walking behavior can be categorized according to walking speed and spatial organization. To interpret these variables correctly, three interrelated levels of analysis must be taken into account: the individual level (personal factors), the external level (external factors), and the group level (social factors) (Aveni, 1977; Feng et al., 2021; Shi et al., 2018).

This chapter contributes to an improved understanding of how speed and the spatial organization of pedestrians vary at different phases of street crossings, when walking in social groups. The resulting insights are relevant to improve simulation techniques, optimize pedestrian facilities, and assign more realistic values in modeling the operational behavior of pedestrians to develop effective strategies for reducing accidents and improving safety for road users.

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:

- Barón L, Susana F, Sousa E & Freitas, E. (2023). Analysis of Pedestrians' Road Crossing Behavior, in Social Groups. Transportation Research Record. https://doi.org/10.1177/03611981231180206.

4.2. Materials and Methods

The experimental approach employed in this study comprises two main steps: data collection and data analysis. These steps are further divided into the following components: parameter definition, experimental procedure, video recordings, video analysis, data organization, and modelling pedestrian walking behavior, as illustrated in Figure 25. Each of these components are described in detail below.

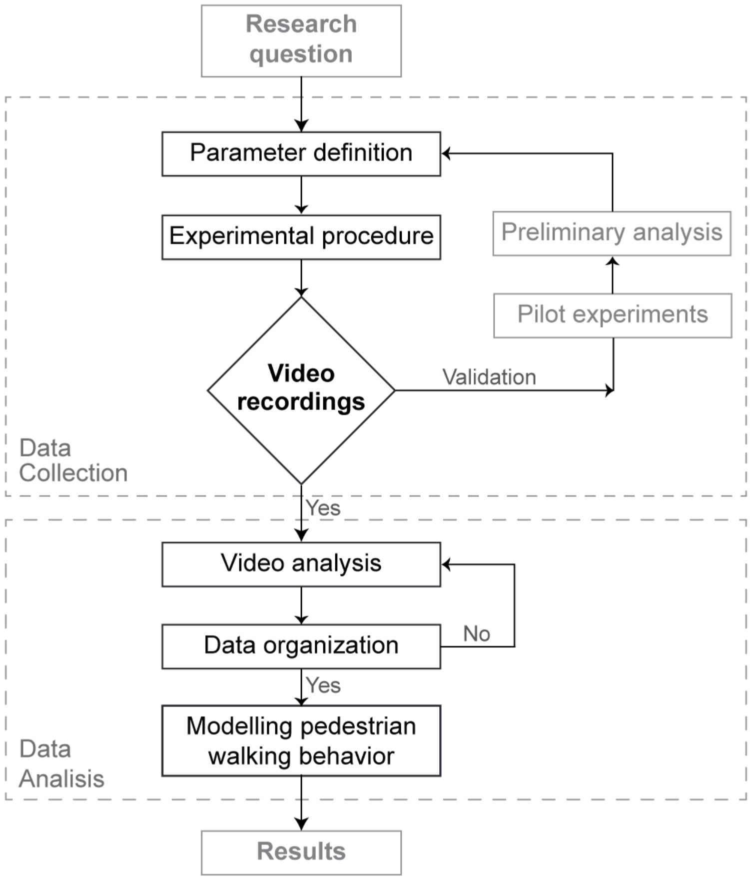


Figure 25. Methodology process steps.

4.2.1. Parameter definition

To define the variables analyzed in this study, the selection of social, personal, and external factors is presented below.

Personal and social factors

In this study, the behavior of pedestrian groups was analyzed, focusing on group size and group sex. The most common sizes observed in Chapter 3 were groups consisting of 1, 2, and 3 people.

Female, male, and mixed groups were considered based on the participants' personal characteristics. Additionally, the participants' leg length was measured as it may have an influence on behavioral coordination.

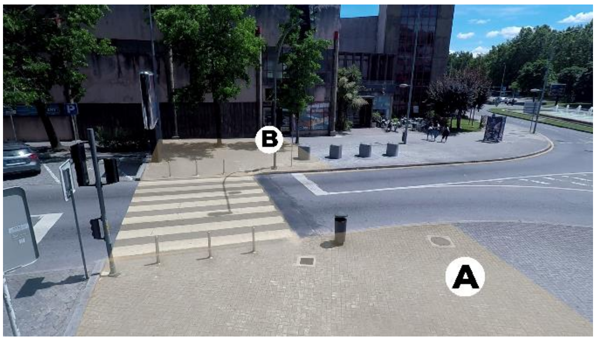
The study recruited 90 adults from the University of Minho community in Portugal. The participants consisted of 45 females and 45 males, with ages ranging from 23 to 43 years old (mean = 27.8 years old; standard deviation = 3.9 years old). Prior to the experiments, all participants provided informed consent. Demographic information, including sex and age, was recorded for each participant. Furthermore, leg length measurements were taken, with a minimum of 0.82 m, maximum of 1.20 m, mean of 0.95 m, and standard deviation of 0.078 m. Detailed information is provided in Appendix A.

Given that all participants fell within the same age range of young adults, the factor of age was not analyzed in this study due to the lack of variability.

External factors

The experiments were conducted in unsignalized crosswalks in an urban area, namely on three streets in Guimarães, Portugal: Teixeira de Pascoais street, Martins Sarmento square, and Doutor Joaquim de Meira street (see Figure 26).

Site S1



Site S2

Site S3

Figure 26. Study section: Site S1 - Teixeira de Pascoais Street; Site S2 - Martins Sarmento Square; Site S3 - Doutor Joaquim de Meira Street, Guimarães, Portugal.

The three streets being studied have varying sidewalk and crosswalk widths, as well as different numbers and placements of obstacles. Each street is a collector road without traffic lights, with two lanes, and mixed land use that includes both commercial and residential properties. A reasonable volume of pedestrian traffic is observed on these streets, resulting in a level of service (LOS) A on the sidewalks according to the Highway Capacity Manual (HCM) 2010 reference values (The & Academies, 2010). Table 10 presents the main characteristics and features of the streets. The infrastructure characteristics were measured on-site.

Table 10 – Main characteristics of the study sites.

Characteristics	**Study Site**		
	S1	**S2**	**S3**
Road pavement	Asphalt concrete	Cobblestones	Asphalt concrete
Distance to a bus stop (m)	99.13	9.75	1.2
Park on street (legal)	yes	no	no
Width of the crosswalk (m)	5.12	2.983	3.994
Length of the crosswalk (m)	7.13	7.994	8.790
Average width of the lanes (m)	2.950	3.265	2.570
Width of the sidewalk A (SA) (m)	8.160	1.900	1.535
Width of the sidewalk B (SB) (m)	9.804	2.000	1.457
Pedestrian volume (15-min)	65	42	28
Pedestrian unit flow rate (p/min/m)	0.565	1.234	0.802

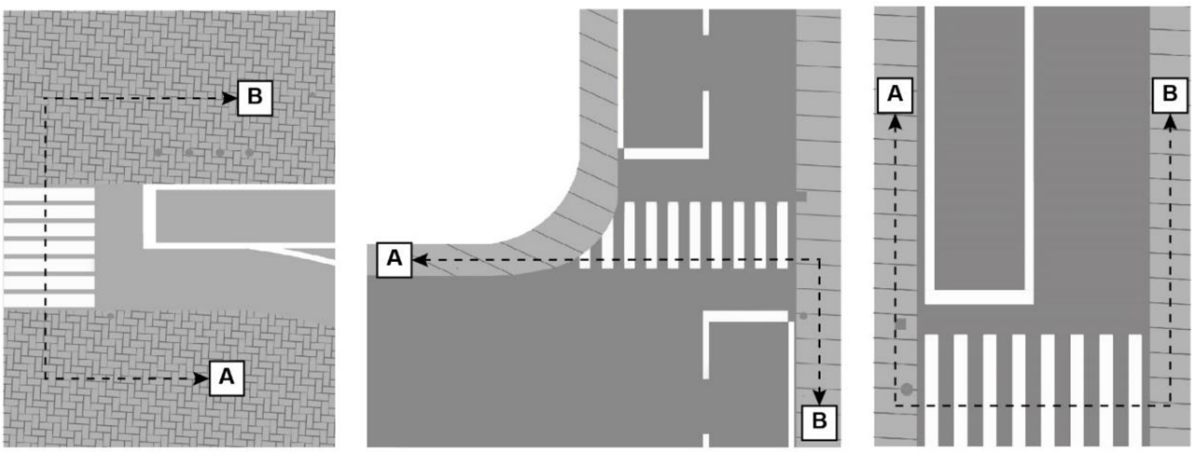
To characterize the space occupied by obstacles on the sidewalks, the effective width was calculated according to HCM, that defines it as the total walkway width minus the width of unusable buffer zones along the curb and building line (HCM 2010). The widths and shy distances from obstructions considered are presented in Table 11.

Table 11 – Effective walkway width.

Site	Sidewalk	Total walkway width (m)	Widths and shy distances from obstructions on the walkway (m)					Effective walkway width (m)
			Building face	Waste baskets	Light pole	Traffic signs	Trees	
S1	SA_1	8.160	0.700	0.900				6.560
	SA_2	8.160	0.700		0.800	0.800		6.660
	SB_1	9.804	0.700			0.800	1.200	7.104
	SB_2	9.804	0.700	0.900	0.800		1.000	6.404
S2	SA_1	1.444				0.800		0.644
	SA_2	2.356						2.356
	SB_1	2.000		0.900				1.100
	SB_2	2.000				0.800		1.200
S3	SA_1	1.535						1.535
	SA_2	1.535			0.800			0.735
	SB_1	1.457						1.457
	SB_2	1.457						1.457

4.2.2. Experimental procedure

For the experiment, participants were asked to walk a fixed trajectory, from predefined point A to B and vice versa (returning from de point B to point A), see Figure 27.



(a) (b) (c)

Figure 27. Pedestrians' trajectories in study sections: (a) site S1; (b) site S2; (c) site S3.

The circuits included an initial part where participants walk on the sidewalk, followed by a road cross in a crosswalk, then back to the sidewalk on the other side of the road. At the end of the trajectory, the pedestrians were instructed to return to the starting point, executing the inverse path.

For each experiment, a cluster of 5 participants was requested to participate. Half of the clusters consisted of three males and two females (type 1), while the other part consisted of three females and two males (type 2) (Figure 28).

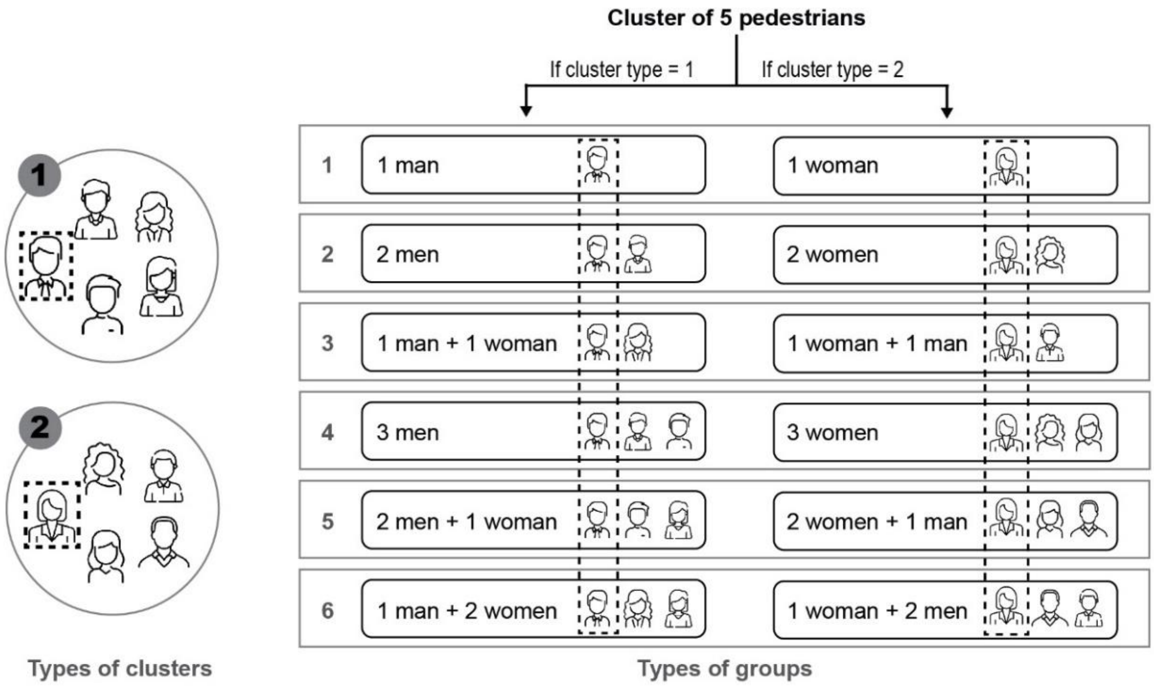


Figure 28. Types of clusters and types of groups.

Each cluster was then organized into six experimental groups formed by either a single person, two dyads, or three triads. To analyze the influence of social factors on individual behavior, one participant was kept fixed as the cluster's reference person and was part of all its groups. The composition of the remaining participants in the group, in terms of their sex and number, was varied across the six experimental groups. This allowed to study how the behavior of the reference person was influenced by different social factors in the group. In cluster type 1, the reference person was a man, while in cluster type 2, it was a woman.

Following the experimental procedure, each of the six small groups walked the predetermined trajectory repeating it twice in each experiment. The experiments lasted approximately 40 minutes. A total of eighteen clusters took part in the study (six clusters per study site), divided into 18 singles, 24 dyads, and 36 triads.

4.2.3. Video recordings

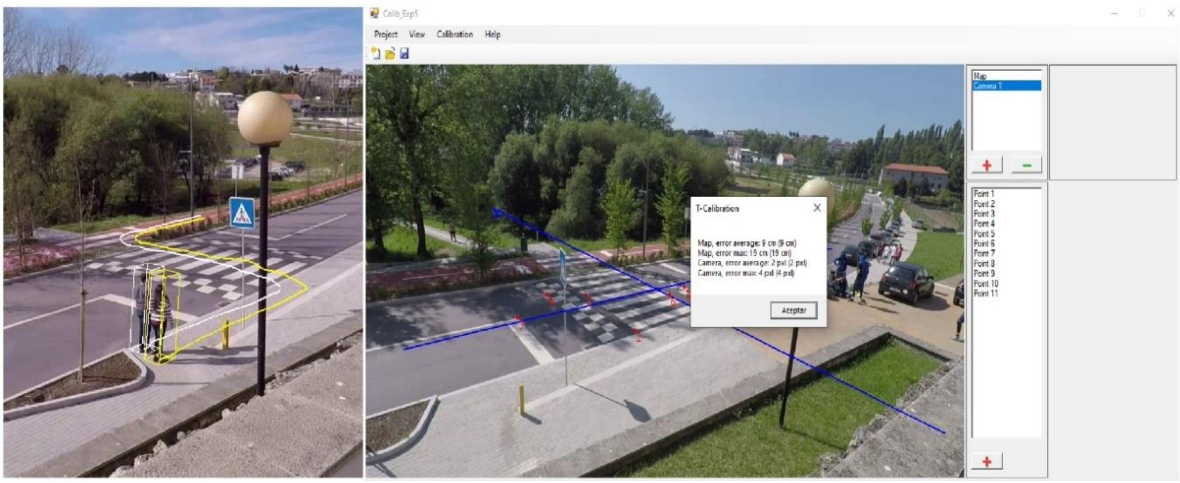
The experimental trials were recorded using a GoPro Hero5 black video camera with a resolution of 1920×1080 pixels, a frame rate of 60 fps, and linear range. The camera was placed at a height between 2.5 and 4 meters and between 2 and 10 meters away from the crosswalk, depending on the conditions of each observation site.

Videos of crowd scenes present challenging problems in computer vision. High object-densities in real-world situations make individual object recognition and tracking impractical (Solmaz et al., 2012). Manual tracking was chosen to overcome the obstacles that represented potential pedestrian occlusions and reduce the error of distances between the pedestrians walking in groups.

4.2.4. Video analysis

Following the experiments, the video recordings were analyzed using T-Analyst (Figure 29 (a)). This is a semi-automated video analysis software developed at Lund University and available as freeware (Johnsson et al., 2018a). This tool has been used in several road safety studies (Bulla-Cruz et al., 2020; Johnsson et al., 2021; Pokorny et al., 2021).

The software calculates the trajectories (x and y coordinates) and the speed of the pedestrians. Calibrations were made in a standalone software named T-Calibration using the TSAI-calibration algorithm (Tsai, 1987) (Figure 29 (b)).

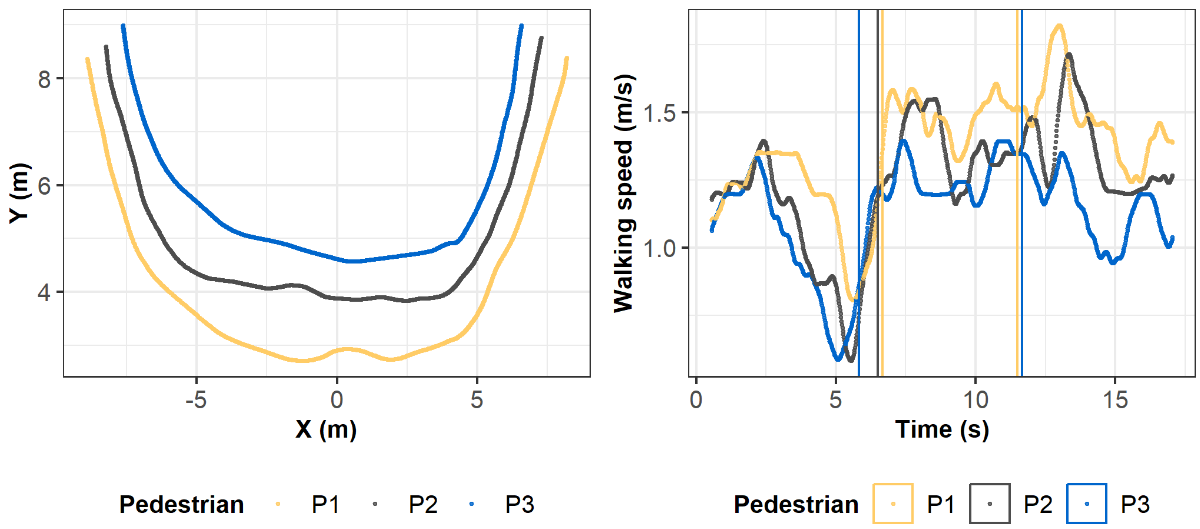


(a) (b)

Figure 29. Example of pilot experiment (a) tracking using T_Analyst and (b) calibration using T_Calibration.

After defining the experimental procedure to be followed in each experience, the data collection method (video recordings) and the software for video analysis (T-Analyst), two pilot experiments were conducted to perform a preliminary analysis and validate the entire experimental protocol.

Figure 30 presents an example of the graphs of pedestrians' trajectories and speed that can be obtained from the data after tracking with the T-Analyst software. Figure 30 (a) shows the path taken by 3 pedestrians from point A to point B as indicated in the experimental protocol. Examples of trajectory and velocity graphs for two complete experiments are presented in appendix B.



(a) (b)

Figure 30. Example of data from group of 3 pedestrians (a) trajectories (b) walking speed.

Figure 30 (b) displays the walking speed of these pedestrians versus the relative duration of the trial. The vertical lines in this graph indicate the moments when each pedestrian first enters the crosswalk (cluster of three lines at the left side of image) and then completes (cluster of three lines at the right side of image) the crossing and arrives at the sidewalk on the other side of the street.

The geometric center coordinates obtained for each participant were utilized to calculate the distances and angles between each pair of pedestrians, as depicted in Figure 31. The process encompassed the following steps: firstly, the order of the pedestrians was determined from left to right, and labels P1 - P2 - P3 were assigned accordingly. Next, the distances between each pair of pedestrians were calculated, and the angles were measured with respect to the direction of movement as the reference.

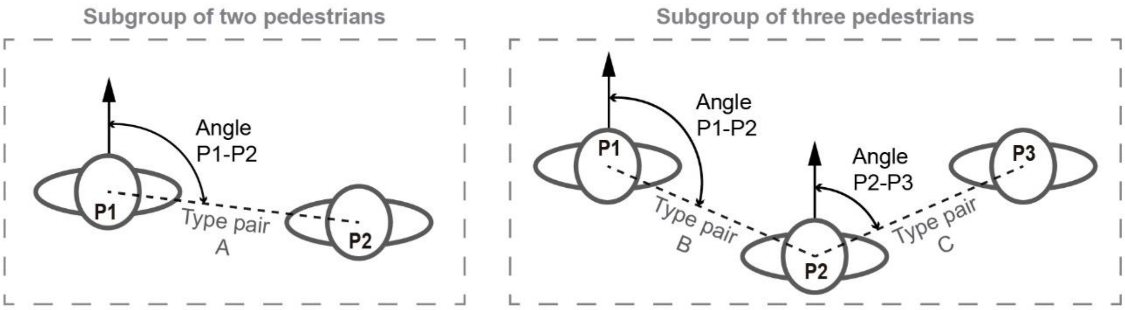


Figure 31. Distances ang angles between pedestrians.

4.2.5. Data organization

The pedestrians' trajectories were split into three analysis phases: (i) before the crossing, (ii) during the crossing, and (iii) after crossing. The path of analysis is shown in Figure 32, which includes the width of each zone of sidewalks or crosswalks according to the study site. Additionally, it includes the length of 9 meters for sidewalks and the length of each crosswalk. Each phase was divided into two segments to study possible differences in the areas closest to the road crossings, before (segment B1, B2), during (segment D1 e D2) and after (segment A1 e A2) the road crossing.

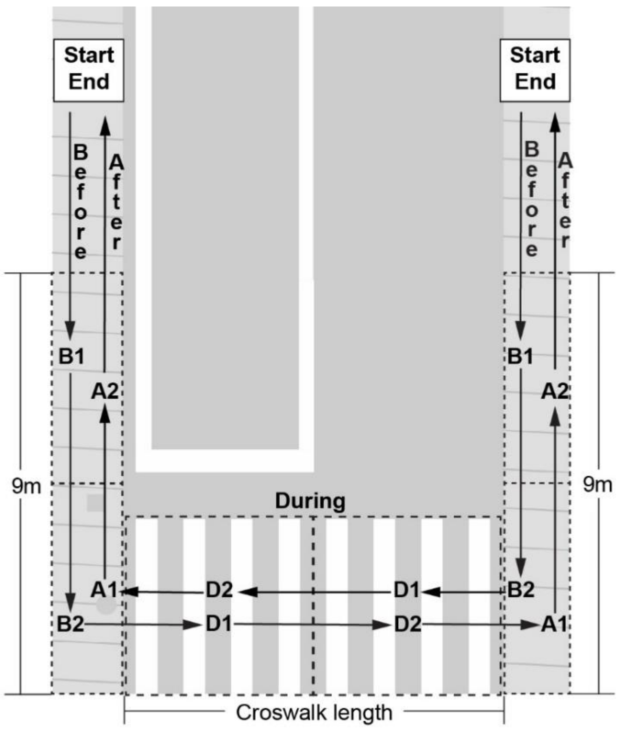


Figure 32. Area of analysis: crossing phases divided in segments.

The final dataset includes the dependent and independent variables. The dependent variables, which were calculated in the segments of each phase, were the average walking speed, average distance and average angles between pairs of pedestrians. The independent variables correspond to the factors identified in the literature that influence the pedestrians' behavior and were divided according to the social and external factors (see Table 12). Personal characteristics are implicit within social factors (sex of pedestrians and leg length).

Table 12 – Description of independent variables used in the study.

	Description variable	**Abbreviation**
External factors	Study site	Site
	Phase: before (B1 e B2), during (D1 e D2) and after (A1 e A2) the road crossing	Phase
	Effective width of zone (sidewalks or crosswalk) of each study site (m)	Width
	Average lane width (m)	W_Lanes
	Crosswalk length (m)	L_Crosswalk
	Presence of parked vehicles: yes or no	Parked
	Road pavement: asphalt concrete or cobblestones	Pav
	Distance from the crosswalk to the nearest intersection (m)	Dist
	Approaching vehicles: yes or no	Veh
	Interaction with other pedestrians: yes or no	Ped
Social factors	Sex composition of the group of participants: female, male and mix	Sex
	Size group: 1, 2, or 3 pedestrians	Size
	Difference between the length of the legs of each pair of pedestrians	D_Leg

Figure 33 shows a summary scheme of the groups of factors considered to study their influence on pedestrian behavior, the variables analyzed, and the analysis phases.

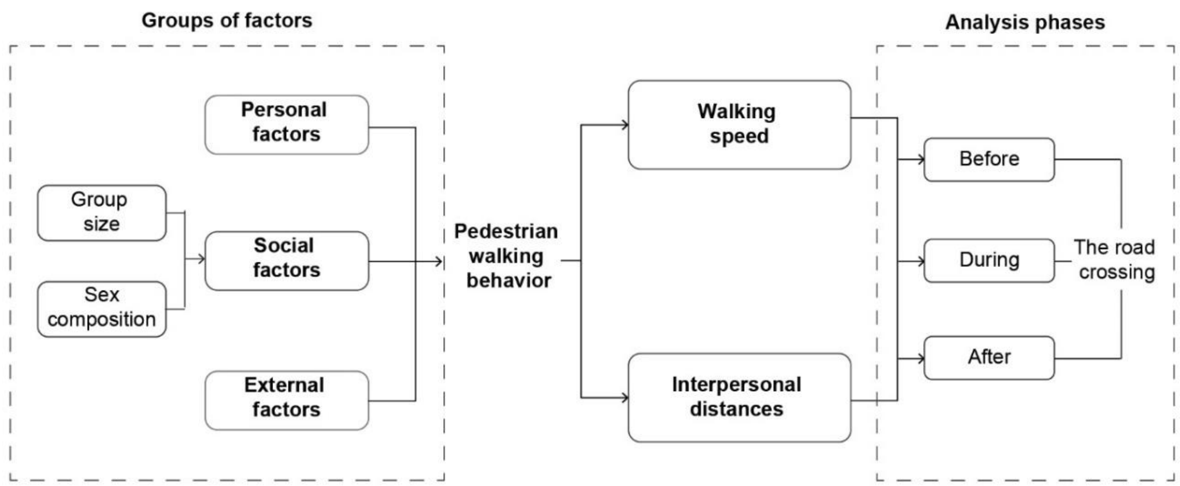


Figure 33. Pedestrian walking behavior analysis scheme.

4.2.6. Modelling pedestrian walking behavior

In this study, a frequentist approach was selected, specifically linear mixed models (LMMs), as they are aligned with the data characteristics and research question and have proven effective in modeling multilevel data on pedestrians' crossing behaviors (Aghabayk et al., 2021).

This class of models is primarily used to describe linear relationships between a response variable and some covariates in grouped data according to one or more factors. LMMs incorporate fixed effects, which are parameters associated with an entire population or with certain repeatable levels of factors, and random effects, which are associated with individual experimental units drawn at random from a population (Pinheiro & Bates, 2000).

LMMs are an appropriate technique for analyzing nested structured data, such as the data presented in this study, due to repeated measurements. The participants were divided into small groups, and each small group walked twice the predefined trajectory (see section 4.2.2. - Experimental procedure). LMMs were estimated to assess the influence of all the variables mentioned above (see Table 12) on the distance between pedestrians and the pedestrians' walking speed.

The hierarchical data structures have three levels (see multilevel diagrams Figure 34). Each observation corresponds to a trajectory of a pair of pedestrians (Pair_ID) for the distance between pedestrians and, of each pedestrian (Ped_ID), for the walking speed. These form part of an upper-level group of participants (Cluste_ID).

The model, for $i = 1, \dots, m; j = 1, \dots, m\_i, k = 1, \dots, m\_ij$ can be written as

$$Y_{ijk} = \beta_O + \sum_{p=1}^{P} \beta_p X_{pijk} + \sum_{l=1}^{L} \alpha_l Z_{li} + u_{ij} + b_i + \varepsilon_{ijk} \tag{1}$$

$$u_{ij} \sim N(0, \sigma_U^2)$$

$$b_i \sim N(0, \sigma_I^2)$$

$$\varepsilon_{ijk} \sim N(0, \sigma_E^2)$$

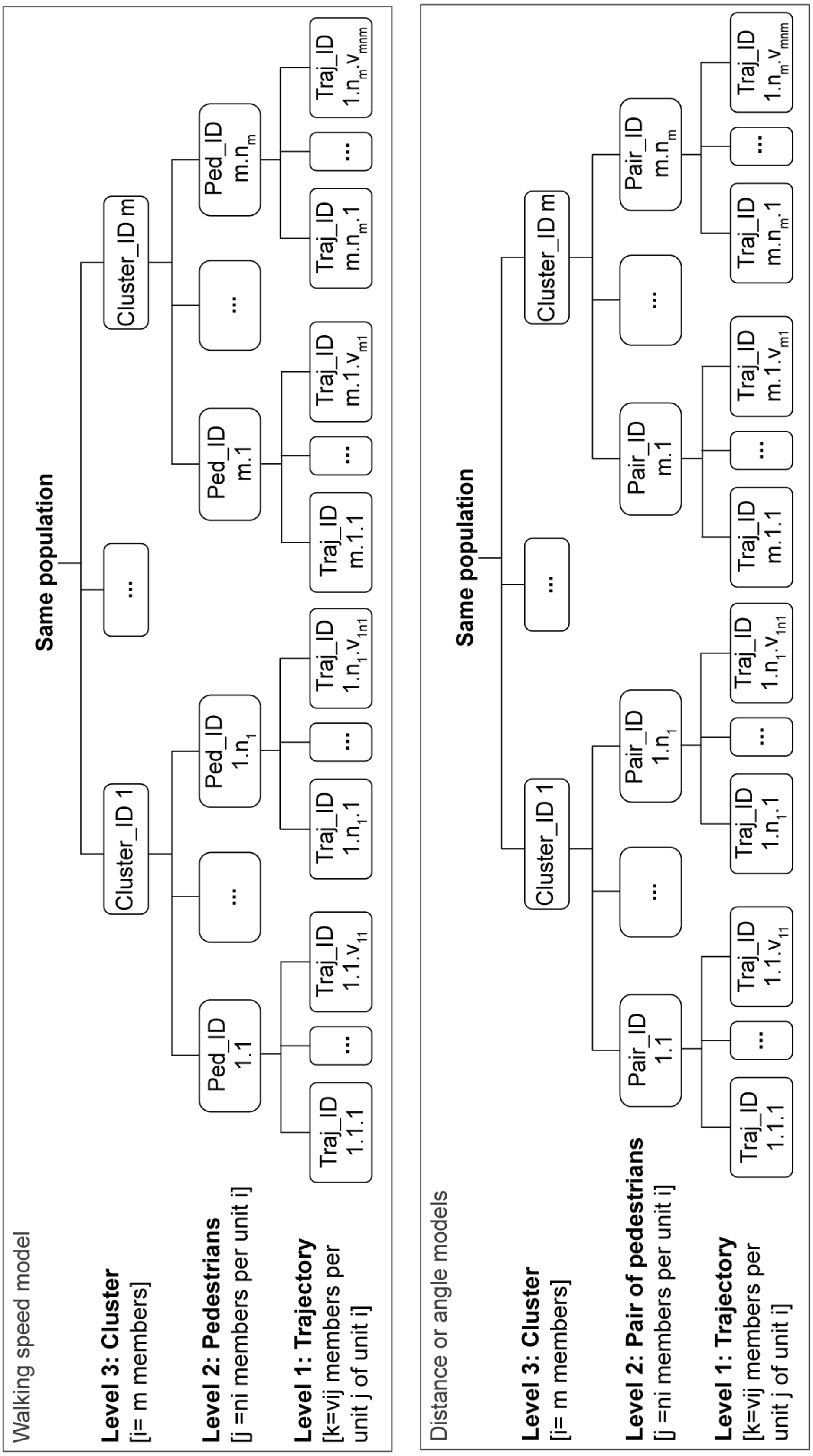


Figure 34. Multilevel diagram of walking speed, distance and angles models.

Where Y_{ijk} is the response variable (pedestrians speed or distance between pedestrians) for the *k-th* trajectory from the *j-th* pedestrian or pair of pedestrians of the *i-th* group of participants, X_{Pijk} is the corresponding value of *p-th* predictor variable at trajectories' level and Z_{li} is the corresponding value of *l-th* predictor variable at group level. ε_{ijk} is the zero mean gaussian error, σ^2_I is the component of variation due to variability among groups, σ^2_U is the component of variation due to variability among pedestrian (or pair of pedestrians) nested within groups, and σ^2_E is the component of residual variability in the repeated measurements within pair of pedestrians or pedestrians. The usual assumptions are made about the random effects: u_{ij} and b_i are assumed to be Gaussian distributed and uncorrelated across the levels.

The variance inflation factor (VIF) was used to verify that there was no multicollinearity among the independent variables. It was found that none of the independent variables in the models for walking speed and pedestrian distance had a VIF greater than 5 (S. G. Singh & Kumar, 2021). Variance components are used to calculate the intraclass correlation (ICC), a statistic that quantifies the degree to which data at the lower level are correlated (Monsalves et al., 2020). The ICC, also referred to as the variance partition coefficient (VPC), is obtained as the proportion of random effects variance over the total variation and it ranges from zero to one.

ICC_1 quantifies the correlation among all the values between and within pairs of pedestrians (distance) or each pedestrian (speed) nested within groups and is given by:

$$ICC_1 = \sigma_I^2/(\sigma_I^2 + \sigma_U^2 + \sigma_E^2) \tag{2}$$

Similarly, ICC_2 quantifies the correlation among the repeated measurements within pairs of pedestrians (distance) or each pedestrian (speed) nested within groups and is given by:

$$ICC_2 = (\sigma_I^2 + \sigma_U^2)/(\sigma_I^2 + \sigma_U^2 + \sigma_E^2) \tag{2.1}$$

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 walking speed and distance between pair of pedestrians, presents the independent variables that were statistically significant to a level of 5 %. All statistical analyses were performed using the R statistical software (R Core Team, 2021).

4.3. Results

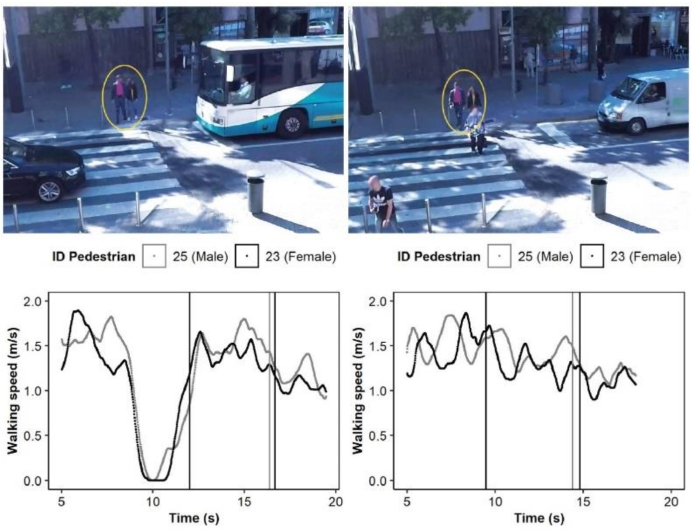
In each experimental, denoting one video per experiment, data were collected from a total of 56 pedestrian trajectories. This was achieved through the utilization of a semi-automatic analysis program, with each video analysis consuming approximately 200 hours.

The experiments were carried out from May 17 to July 8, 2019, exclusively on weekdays (Monday to Friday) and within standard working hours (9 a.m. to 12 p.m. and 2 p.m. to 6 p.m.). This deliberate scheduling aimed to mitigate potential atypical conditions related to peak vehicular or pedestrian traffic hours. All three previously introduced study locations were included in this investigation, adhering to the comprehensive experimental procedure outlined.

To study the pedestrian behavior when crossing the road in a group, three separate models were developed for the dependent variables: (i) the average walking speed of each participant (see section 4.3.1), for (ii) the average distance between pairs of participants (section 4.3.2), and for (iii) the average angle of participants pairs (section 4.3.3).

4.3.1. Average walking speed

Traffic regulations in Portugal require that drivers cede passage to pedestrians when approaching a crosswalk without traffic lights. However, in 5% of the study's sample, drivers did not adhere to this regulation, resulting in pedestrians having to wait for the car to pass. Two trajectories with the same participants are shown in Figure 35.



(a) (b)

Figure 35. Differences between pedestrians' speed: (a) The vehicle did not stop; (b) The vehicle stopped.

One can observe that in the first case (Figure 35(a)), the vehicle did not stop, forcing pedestrians to considerably reduce their speed compare with the second trajectory (Figure 35 (b)). Only trajectories in which drivers complied with traffic regulations were selected for analysis (5,676 observations).

Table 13 presents summary statistics for pedestrians' walking speed, as a function of social and external factors. On average, the highest walking speed was observed for isolated individuals rather than those in groups, male groups, in the absence of approaching vehicles, and during road crossings.

Table 13 – Descriptive statistics of the walking speed.

Group of factors	Variable (Abbreviation)	Levels		Walking speed (m/s)			
				Min	**Max**	**Mean**	**SD**
Social factors	Size group (Size)	1		0.897	1.978	1.435	0.184
		2		0.660	2.000	1.318	0.176
		3		0.452	1.922	1.253	0.197
	Sex composition of the group of participants (Sex)	Female		0.581	1.880	1.278	0.204
		Male		0.683	1.978	1.329	0.196
		Mix		0.452	2.000	1.270	0.191
External factors	Study site (Site)	S1		0.581	2.000	1.289	0.211
		S2		0.622	1.857	1.272	0.178
		S3		0.452	1.900	1.293	0.200
	Crossing phase (Phase)	Before	B1	0.737	1.821	1.270	0.178
			B2	0.452	1.806	1.158	0.216
		During	D1	0.789	1.900	1.360	0.169
			D2	1.019	1.931	1.372	0.138
		After	A1	0.612	2.000	1.287	0.214
			A2	0.688	1.879	1.259	0.173
	Approaching vehicles (Veh)	Yes		0.452	2.000	1.274	0.201
		No		0.612	1.900	1.305	0.186
	Interaction with other pedestrians (Ped)	Yes		0.622	2.000	1.249	0.200
		No		0.452	1.978	1.290	0.195
	Presence of parked vehicles (Parked)	Yes		0.452	1.978	1.267	0.198
		No		0.612	2.000	1.291	0.196

The pedestrians' walking speed was estimated using a LMM. Random effects were considered for pedestrian and group of participants, to account for repeated measurements. Significant effects of variables on walking speed were observed based on Satterthwaite's test (Table 14). Significant predictor variables and interactions are discussed below.

Table 14 – Satterthwaite's test results for the model for the pedestrian's average speed.

Variables	**Sum Sq**	**Num DF**	**F value**	**p-value**
Size	6.271	2.000	145.144	<0.001
Sex	0.507	2.000	11.729	<0.001
Phase	12.256	5.000	113.474	<0.001
Ped	0.039	1.000	1.824	0.177
Parked	0.202	1.000	9.345	0.002
Veh	0.428	1.000	19.817	<0.001
Width	1.145	1.000	53.008	<0.001
Dist	0.121	1.000	5.606	0.028
Size × Phase	0.457	10.000	2.118	0.020
Size × Ped	0.333	2.000	7.718	<0.001
Size × Parked	0.348	2.000	8.049	<0.001
Sex × Phase	0.838	10.000	3.880	<0.001
Sex × Ped	0.159	2.000	3.683	0.025
Sex × Parked	0.205	2.000	4.736	0.009
Sex × Veh	0.219	2.000	5.064	0.006
Phase × Veh	1.288	5.000	11.928	<0.001
Phase × Parked	0.895	5.000	8.282	<0.001
Parked × Veh	0.081	1.000	3.737	0.053

The final model includes all significant predictor variables (Equation 3). Non-significant social factor was *D_Leg* (legs length) and, external factors were *Site* (study site), *Pav* (pavement), *W_Lanes* (lane width), *L_Crosswalk* (crosswalk length).

For $i = 1, \dots, 5; j = 1, \dots, 18; k = 1, \dots, mij$, the model, can be written as

$$\begin{aligned} WS_{ijk} = \beta_O &+ Size_{ijk} \times Phase_{ijk} \\ &+ Size_{ijk} \times Ped_{ijk} + Size_{ijk} \times Park_{kij} + Sex_{ijk} \times Phase_{ijk} \\ &+ Sex_{ijk} \times Ped_{ijk} + Sex_{ijk} \times Park_{ijk} + Sex_{ijk} \times Veh_{ijk} \\ &+ Phase_{ijk} \times Veh_{ijk} + Phase_{ijk} \times Park_{ijk} + Veh_{ijk} \times Park_{ijk} \\ &+ \alpha Width_{ijk} + \alpha Dist_i + u_{ij} + b_i + \varepsilon_{ijk} \end{aligned} \tag{3}$$

The full summary statistics of the model are presented in Tables 15-17.

Table 15 – Linear mixed model result of average walking speed (variables without interactions).

Variable	**Value of category**	**'Speed' model (n = 5676)**		
		Estimate	**SE**	**p-value**
Group Size	Size_1		Reference	
	Size_2	-0.07	0.022	0.002*
	Size_3	-0.137	0.022	<0.001*
Group sex	Female		Reference	
	Male	0.081	0.02	<0.001*
	Mix	0.002	0.016	0.904
Crossing phase	Phase_B1		Reference	
	Phase_B2	-0.124	0.03	<0.001*
	Phase_D1	0.101	0.03	0.001*
	Phase_D2	0.117	0.031	<0.001*
	Phase_A1	0.043	0.03	0.147
	Phase_A2	-0.029	0.03	0.337
Out-group pedestrians	Ped_No		Reference	
	Ped_Yes	-0.04	0.023	0.084
Parked vehicles	Parked_No		Reference	
	Parked_Yes	0.035	0.021	0.100
Approaching vehicles	Veh_No		Reference	
	Veh_Yes	-0.039	0.014	0.008*
Effective width	Width_E	-0.013	0.002	<0.001*
Distance between crosswalk to the intersection	D_Inter	0.003	0.001	0.028*

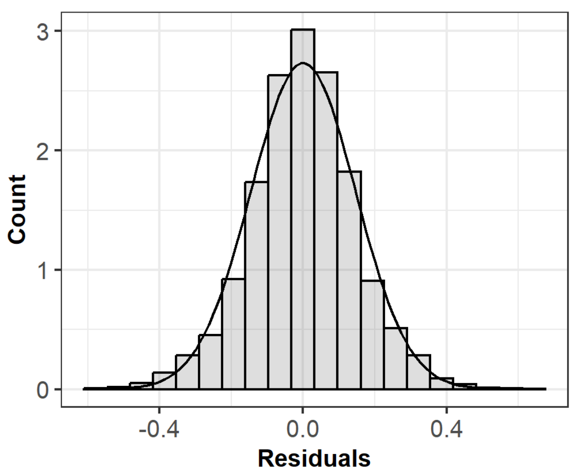
Table 16 – Linear mixed model result of average walking speed (variables with interactions).

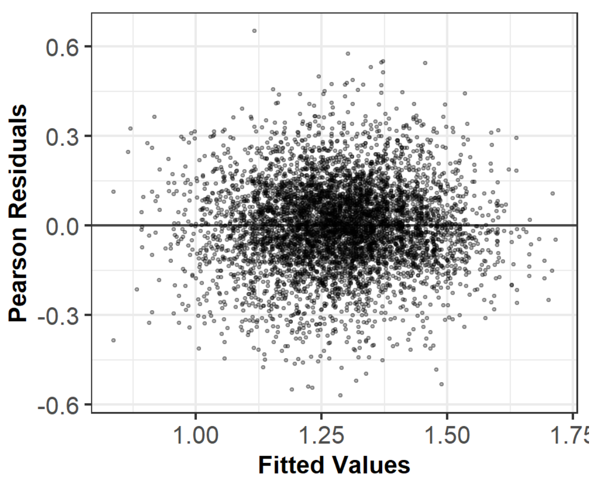
Variable	Value of category	'Speed' model (n = 5676)		
		Estimate	**SE**	**p-value**
Group size × Crossing phase	Size_1:Phase_B1		Reference	
	Size_2:Phase_B2	-0.005	0.030	0.865
	Size_3:Phase_B2	0.000	0.029	0.999
	Size_2:Phase_D1	-0.016	0.030	0.589
	Size_3:Phase_D1	0.024	0.029	0.416
	Size_2:Phase_D2	-0.038	0.030	0.200
	Size_3:Phase_D2	-0.008	0.029	0.795
	Size_2:Phase_A1	-0.066	0.030	0.027*
	Size_3:Phase_A1	-0.065	0.029	0.025*
	Size_2:Phase_A2	-0.002	0.030	0.949
	Size_3:Phase_A2	0.012	0.029	0.675
Group size × Out-group pedestrians	Size_1:Ped_No		Reference	
	Size_2:Ped_Yes	0.034	0.024	0.157
	Size_3:Ped_Yes	-0.018	0.023	0.436
Group size × Parked vehicles	Size_1:Parked_No		Reference	
	Size_2:Parked_Yes	-0.071	0.019	<0.001*
	Size_3:Parked_Yes	-0.072	0.018	<0.001*
Group sex × Crossing phase	Phase_B1:Sex_Female		Reference	
	Phase_B2:Sex_Male	0.042	0.021	0.045*
	Phase_D1:Sex_Male	-0.051	0.021	0.015*
	Phase_D2:Sex_Male	-0.059	0.021	0.005*
	Phase_A1:Sex_Male	-0.025	0.021	0.236
	Phase_A2:Sex_Male	-0.018	0.021	0.396
	Phase_B2:Sex_Mix	0.058	0.018	0.001*
	Phase_D1:Sex_Mix	-0.015	0.018	0.397
	Phase_D2:Sex_Mix	-0.015	0.018	0.409
	Phase_A1:Sex_Mix	-0.009	0.018	0.616
	Phase_A2:Sex_Mix	-0.004	0.018	0.815
Group sex × Out-group pedestrians	Sex_Female:Ped_No		Reference	
	Sex_Male:Ped_Yes	0.046	0.017	0.007*
	Sex_Mix:Ped_Yes	0.023	0.015	0.126
Group sex × Parked vehicles	Sex_Female:Parked_No		Reference	
	Sex_Male:Parked_Yes	-0.033	0.015	0.026*
	Sex_Mix:Parked_Yes	0.004	0.013	0.739
Group sex × Approaching vehicles	Sex_Female:Veh_No		Reference	
	Sex_Male:Veh_Yes	-0.022	0.015	0.138
	Sex_Mix:Veh_Yes	0.014	0.012	0.240

Table 17 – Linear mixed model result of average walking speed (variables with interactions and metrics).

Variable	Value of category	'Speed' model (n = 5676)		
		Estimate	**SE**	**p-value**
Crossing phase × Approaching vehicles	Phase_B1:Veh_No	Reference		
	Phase_B2:Veh_Yes	-0.026	0.015	0.075
	Phase_D1:Veh_Yes	0.014	0.015	0.344
	Phase_D2:Veh_Yes	0.053	0.015	<0.001*
	Phase_A1:Veh_Yes	0.073	0.015	<0.001*
	Phase_A2:Veh_Yes	0.029	0.015	0.047
Crossing phase × Parked vehicles	Phase_B1:Parked_No	Reference		
	Phase_B2:Parked_Yes	-0.018	0.015	0.246
	Phase_D1:Parked_Yes	0.022	0.015	0.152
	Phase_D2:Parked_Yes	0.067	0.015	<0.001*
	Phase_A1:Parked_Yes	0.007	0.015	0.667
	Phase_A2:Parked_Yes	-0.012	0.015	0.436
Parked vehicles × Approaching vehicles	Parked_No:Veh:No	Reference		
	Parked_Yes:Veh_Yes	-0.019	0.01	0.053
ICC1		0.090		
ICC2		0.289		
AIC		-5272.1		

Based on the diagnostic plot for the model described in Equation (3), the histogram of the residuals suggests normality (Figure 36 (a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 36 (b)). The residuals appear to be homogeneously distributed.





(a) (b)

Figure 36. Diagnostic plots - residuals for the model (average speed): (a) Histogram of the residuals; (b) Pearson residual versus fitted values.

One variable that did not exhibit a significant influence on pedestrian speed was the study site. This can be visually verified in Figure 37, where no substantial variations are observed depending on the site. Contrasts were employed to analyze the significant interactions among variables and to compare the levels within each variable. The obtained results were categorized into social and external factors.

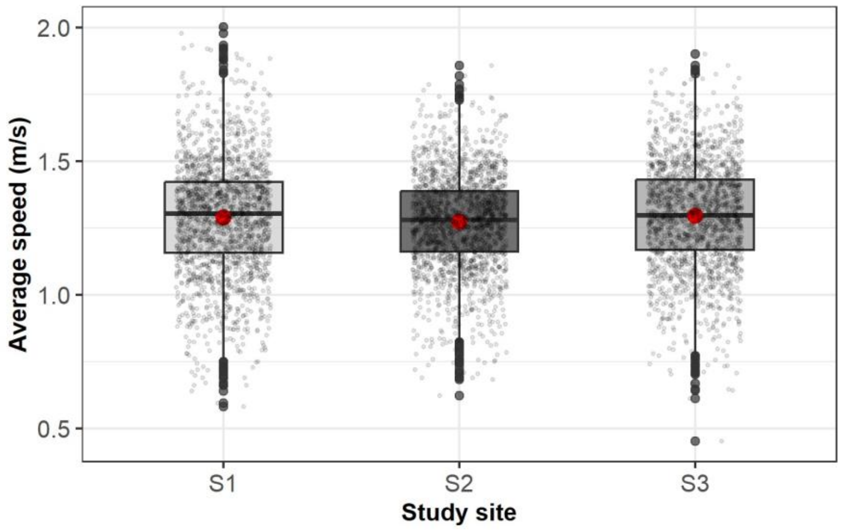


Figure 37. Boxplot of average walking speed of pedestrians as a function of study site.

4.3.1.1. Social factors

The statistically significant interactions between group size and the crossing phase were analyzed using contrasts. As shown in Figure 38, the pedestrians' average speed varied with the crossing phase.

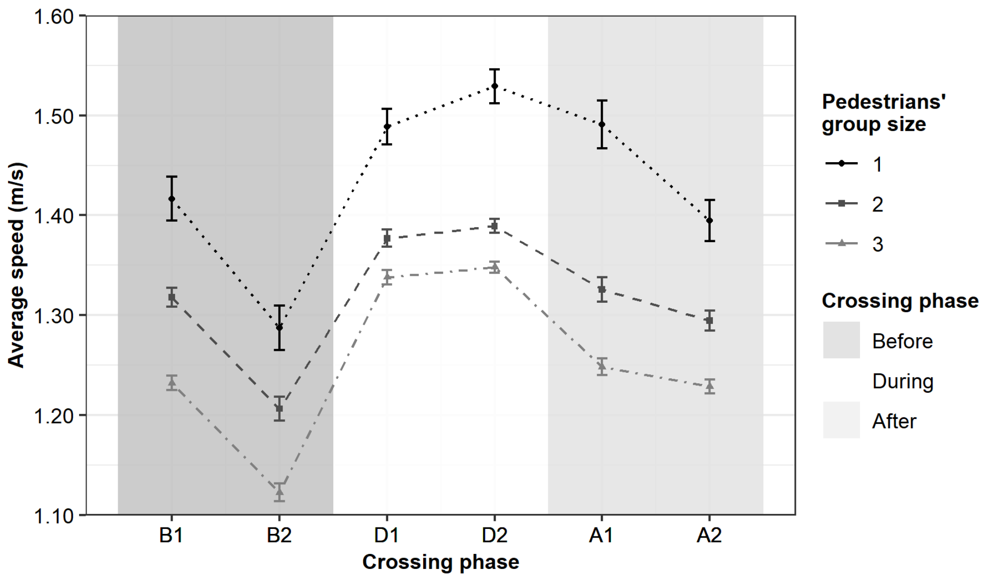


Figure 38. Pedestrians' average speed and respective standard error according to the group size per crossing phase.

The average speed decreased as pedestrians approached the road crossing (B2), increased during the road crossing (D1 and D2), and then decreased as pedestrians returned to the sidewalk on the other side of the street. Notably, the average speed in B1 was similar to that in A2, suggesting that pedestrians return to their comfortable walking speed after crossing.

Figure 38 also revealed that speed depended on group size, with pedestrian speed decreasing as group size increased. The highest speed was observed for singles and the lowest for triads, and this decrease was consistent throughout the phases. Table 18 indicated that the difference between pedestrian speeds according to group size was significant (p-value<0.05) at each crossing phase.

Table 18 – Group size contrasts according to the phase.

Size contrasts	**Phase**	**Estimate**	**SE**	**p-value**
1-2	B1	0.088	0.023	<0.001
	B2	0.093	0.023	<0.001
	D1	0.104	0.024	<0.001
	D2	0.126	0.024	<0.001
	A1	0.154	0.023	<0.001
	A2	0.09	0.024	<0.001
1-3	B1	0.182	0.023	<0.001
	B2	0.182	0.022	<0.001
	D1	0.158	0.023	<0.001
	D2	0.19	0.023	<0.001
	A1	0.247	0.022	<0.001
	A2	0.17	0.023	<0.001
2-3	B1	0.094	0.012	<0.001
	B2	0.089	0.012	<0.001
	D1	0.054	0.013	<0.001
	D2	0.063	0.013	<0.001
	A1	0.093	0.012	<0.001
	A2	0.08	0.012	<0.001

The interactions between variables group size *(Size)* with the presence of out-group pedestrians *(Ped)* and parked vehicles *(Parked)* were also significant (see Figure 39 and 40).

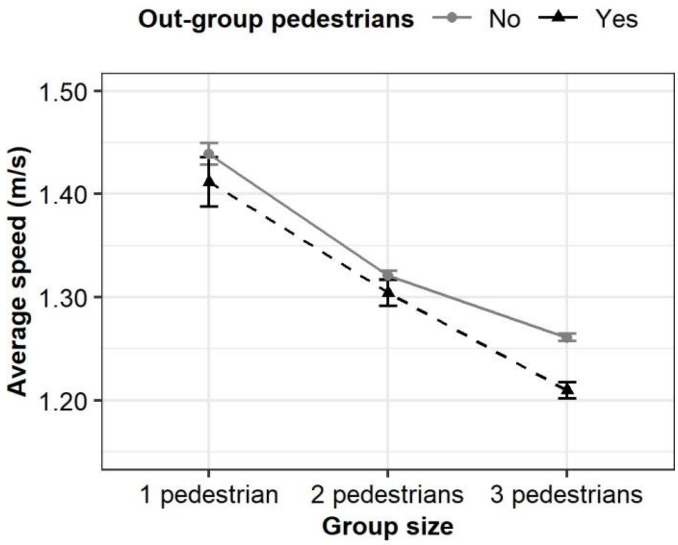


Figure 39. Pedestrians' average speed and respective standard error per group size according to the presence of out-group pedestrians.

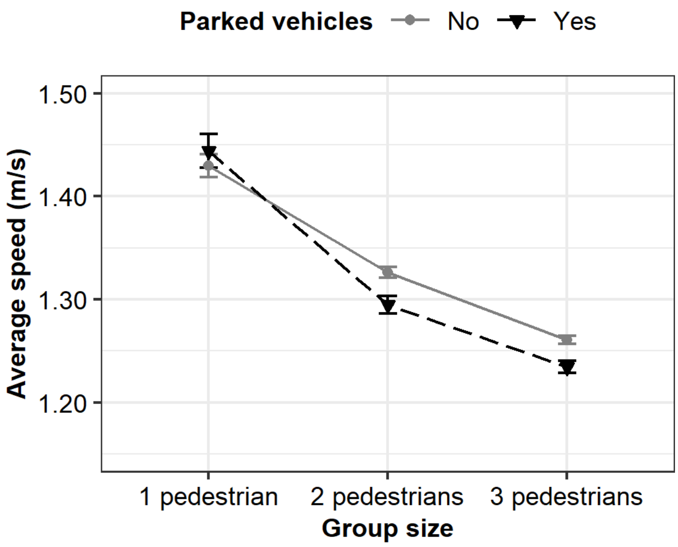


Figure 40. Pedestrians' average speed and respective standard error per group size according to the presence of parked vehicles.

Table 19 presents the contrast comparing the effect of the presence of pedestrians outside the group *(Ped)* and parked vehicles *(Parked)* for each group size *(Size)*. These results reveal that the difference between having or not having interactions with pedestrians outside the group was significant only for triads. In the case of interactions with parked vehicles, it was significant for dyads and triads. Without these interactions, the observed pedestrians' speed was higher.

Table 19 – Contrast of interactions with out-group pedestrians and parked vehicles per group size.

Size	Ped No - Yes			Parked No - Yes		
	Estimate	SE	p-value	Estimate	SE	p-value
1 pedestrian	0.017	0.021	0.437	-0.027	0.017	0.102
2 pedestrians	-0.018	0.011	0.122	0.044	0.009	<0.001
3 pedestrians	0.035	0.008	<0.001	0.045	0.007	<0.001

The average speed also varies according to the group sex (Figure 41). It is important to emphasize that although there was a similar pattern of average speed according to the phases, the pattern of the average speed per group sex was not as homogeneous as per group size.

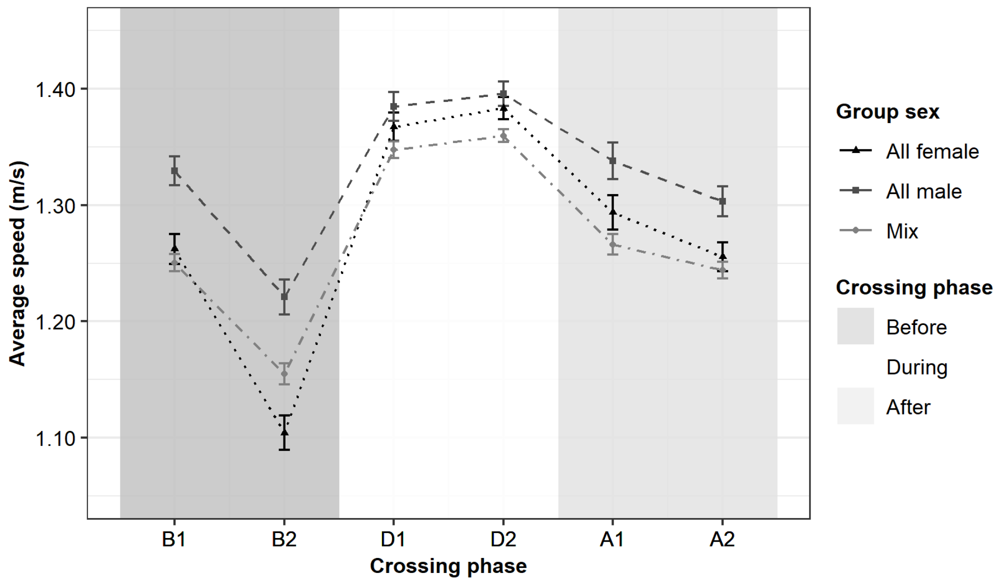


Figure 41. Pedestrians' average speed and respective standard error according to the group sex per crossing phase.

As can be noted in Table 20, there was a clear difference between the average speed of the all-male groups compared to the all-female ones before and after the crossing. The differences between all-female and mixed groups were only significant before the crossing. This could indicate that women tend to slow down even more when deciding to cross, which is why only in this phase there were significant differences from the mixed groups.

Table 20 - Contrasts of the group sex per crossing phase.

Phase	Sex contrasts								
	Female - Male			Female - Mix			Male - Mix		
	Estimate	SE	p-value	Estimate	SE	p-value	Estimate	SE	p-value
B1	-0.077	0.019	0.000	-0.023	0.016	0.307	0.054	0.015	0.001
B2	-0.119	0.018	<0.001	-0.080	0.015	<0.001	0.038	0.015	0.025
D1	-0.026	0.019	0.343	-0.008	0.016	0.875	0.018	0.015	0.457
D2	-0.018	0.019	0.587	-0.008	0.016	0.863	0.010	0.015	0.782
A1	-0.052	0.018	0.011	-0.014	0.015	0.626	0.038	0.015	0.026
A2	-0.059	0.019	0.004	-0.019	0.016	0.450	0.040	0.015	0.020

Regarding the pre-crossing phase (B1 and B2), there was a notable decrease in average speed, particularly among women, as indicated. The speed reduction between B1 and B2 ranged between 8% and 9% for most cases (1, 2, and 3 pedestrians, mixed groups, and all-men), as shown in Table 21.

Table 21 – Pedestrian average speed by the phase according to the group size.

Phase	Size	Average speed (m/s)	SE	Speed variation
B1	1	1.417	0.022	
B2	1	1.287	0.022	-9%
D1	1	1.489	0.018	16%
D2	1	1.529	0.017	3%
A1	1	1.491	0.024	-2%
A2	1	1.395	0.021	-6%
B1	2	1.318	0.01	
B2	2	1.206	0.012	-8%
D1	2	1.377	0.009	14%
D2	2	1.389	0.007	1%
A1	2	1.326	0.012	-5%
A2	2	1.295	0.01	-2%
B1	3	1.232	0.007	
B2	3	1.123	0.009	-9%
D1	3	1.338	0.007	19%
D2	3	1.348	0.006	1%
A1	3	1.248	0.008	-7%
A2	3	1.229	0.007	-2%

However, for female groups, the average speed reduction was 13%, as highlighted in Table 22 (shaded gray). Furthermore, there was a significant increase in average speed between B2 and D1, especially among female groups, where it reached 24%. Although this study did not specifically evaluate the decision-making process for crossing, these results suggest that group sex may be a relevant factor in determining the crossing time.

Table 22 - Pedestrian average speed by the phase according to the group sex.

Phase	Sex	Average speed (m/s)	SE	Speed variation
B1	Female	1.263	0.013	
B2	Female	1.102	0.015	**-13%**
D1	Female	1.366	0.012	**24%**
D2	Female	1.384	0.01	1%
A1	Female	1.294	0.015	-6%
A2	Female	1.256	0.012	-3%
B1	Male	1.329	0.012	
B2	Male	1.219	0.015	-8%
D1	Male	1.385	0.012	14%
D2	Male	1.397	0.011	1%
A1	Male	1.338	0.016	-4%
A2	Male	1.304	0.013	-3%
B1	Mix	1.25	0.007	
B2	Mix	1.147	0.009	-8%
D1	Mix	1.345	0.007	17%
D2	Mix	1.359	0.006	1%
A1	Mix	1.266	0.009	-7%
A2	Mix	1.245	0.007	-2%

Interactions between group sex *(Sex)* and the presence of out-group pedestrians *(Ped)*, parked vehicles *(Parked)* and approaching vehicles *(Veh)* were also found to be significant. As indicated by the model (see also Figure 42), the speed increase in the female groups was significant when there were no out-group pedestrians compared to when there were ($\hat{\beta}$=0.034, SE=0.013, p-value 0.009). The difference between having or not having interactions with out-group pedestrians was not significant for the other groups' sex compositions (p-value >0.05). Mixed ($\hat{\beta}$=0.011, SE=0.012, p-value 0.330) and male ($\hat{\beta}$=-0.012, SE =0.013, p-value 0.343).

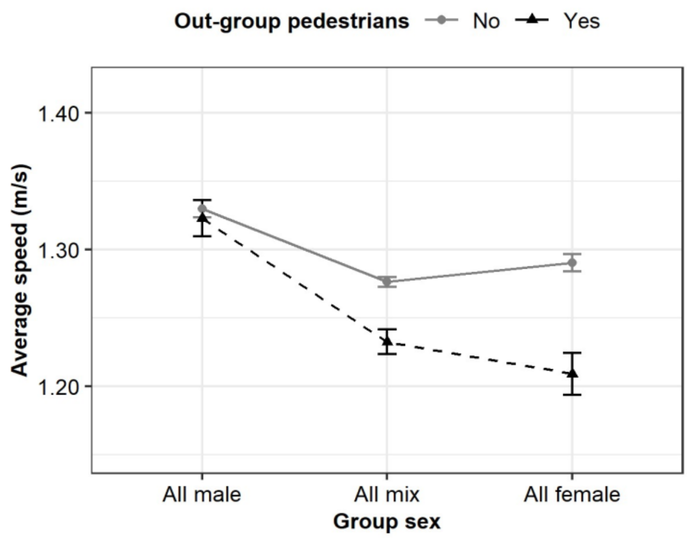


Figure 42. Pedestrians' average speed and respective standard error per group sex according to interaction with out-group pedestrians.

In the male groups, the increase in speed was significant when there were no parked vehicles versus when there were parked vehicles ($\hat{\beta}$=0.034, SE=0.013, p-value 0.009) (Figure 43). For the other groups' sex compositions, the difference on the average speed was not significant (p-value >0.05). Mixed ($\hat{\beta}$=0.007, SE=0.009, p-value 0.434) and female ($\hat{\beta}$=0.011, SE =0.011, p-value 0.309).

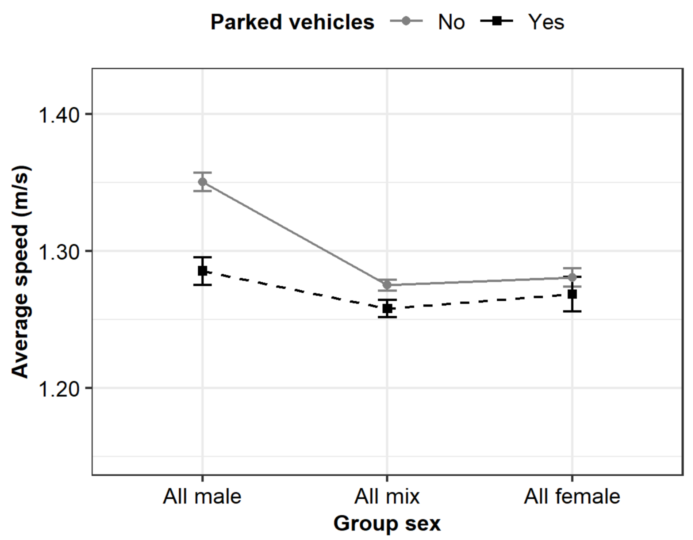


Figure 43. Pedestrians' average speed and respective standard error per group sex according to presence of parked vehicles.

Finally, in male ($\hat{\beta}$=0.046, SE=0.010, p-value <0.001) and female ($\hat{\beta}$=0.024, SE=0.011, p-value 0.032) groups, the increase in speed was significant when no vehicle was approaching (Figure 44). For the mixed group, the difference on the average speed was not significant ($\hat{\beta}$=0.010, SE=0.007, p-value 0.131).

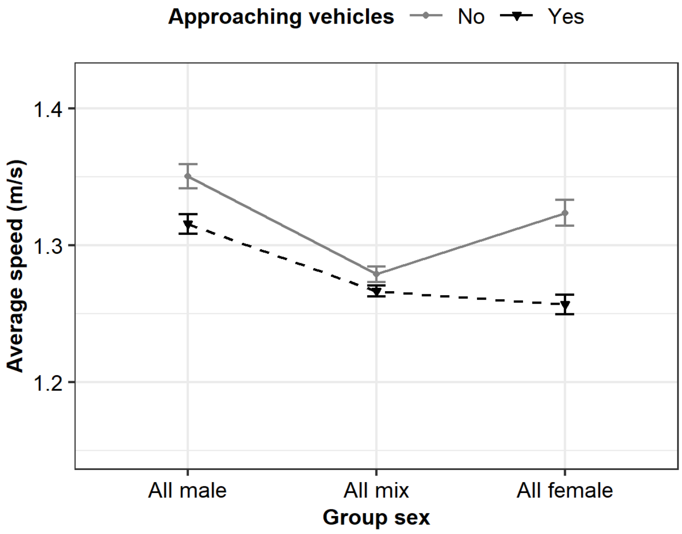


Figure 44. Pedestrians' average speed and respective standard error per group sex according to presence of approaching vehicles.

4.3.1.2. External factors

In terms of the external factors influencing pedestrian walking speed, the interaction between approaching vehicles *(Veh)* and parked vehicles *(Parked)* was significant, as were the interactions between approaching *(Veh)* and parked vehicles *(Parked)* with the crossing phase *(Phase)*.

On the one hand, the model results show that differences in the pedestrians' speed with or without parked vehicles were significant only when the vehicles approached ($\hat{\beta}$=-0.031, SE=0.008, p-value <0.001). When there were no approaching vehicles, the effect of parked vehicles was not significant ($\hat{\beta}$=-0.011, SE=0.009, p-value=0.229) (see Figure 45).

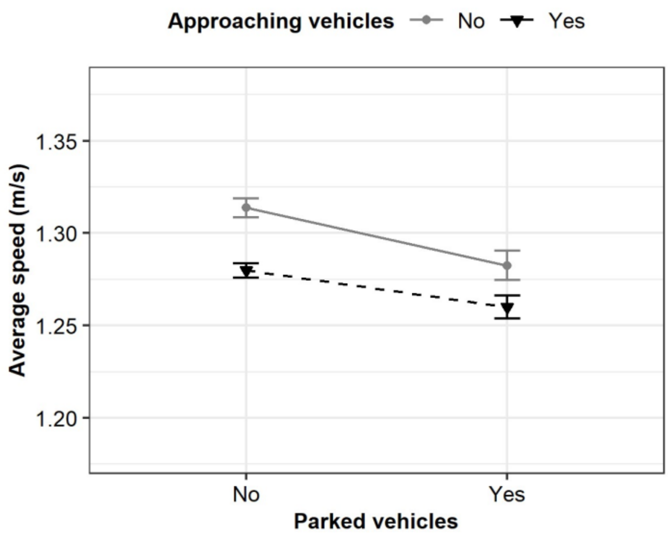


Figure 45. Pedestrians' average speed and respective standard error according to the presence of approaching vehicles per presence of parking vehicles.

On the other hand, in the interactions between approaching and parked vehicles with the crossing phase, as shown in Figure 46 and 47, there was a similar pattern in both cases, according to the crossing phase. This pattern was similar to the one mentioned previously: speed reduction before the crossing, speed increase during the crossing, and decrease again after the crossing. The results of the contrasts used to analyze these interactions are presented in Table 23.

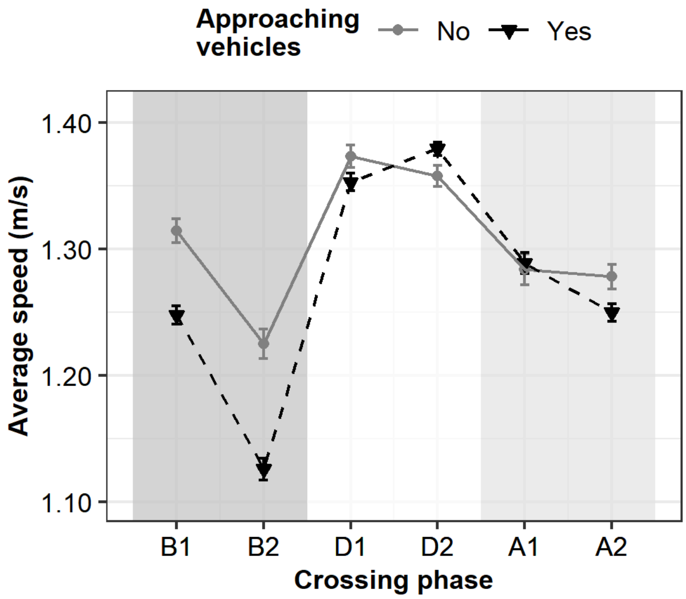


Figure 46. Pedestrians' average speed and respective standard error per crossing phase according to presence of approaching vehicles.

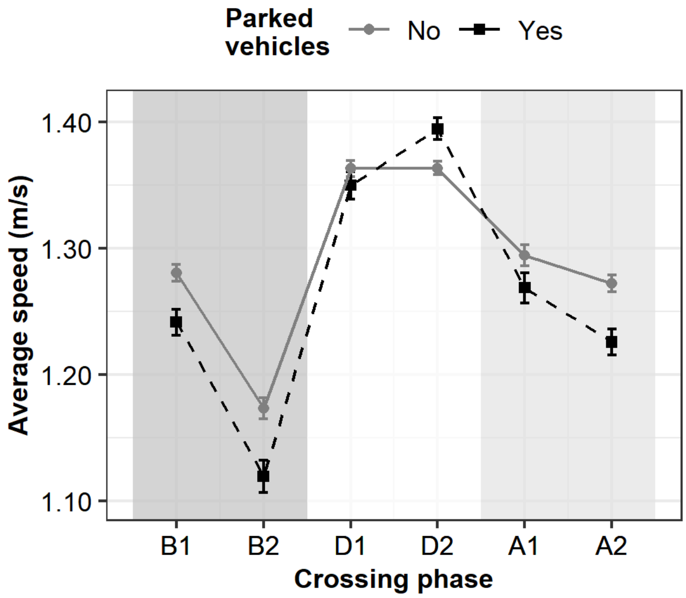


Figure 47. Pedestrians' average speed and respective standard error per crossing phase according to presence of parked vehicles.

Table 23 – Approaching vehicles and parked vehicles contrasts according to the phase.

Phase	Veh			Parked		
	No - Yes			No - Yes		
	Estimate	SE	p-value	Estimate	SE	p-value
B1	0.051	0.011	<0.001	0.032	0.012	0.008
B2	0.077	0.011	<0.001	0.050	0.012	<0.001
D1	0.037	0.012	0.002	0.010	0.012	0.402
D2	-0.002	0.012	0.866	-0.036	0.012	0.003
A1	-0.022	0.011	0.048	0.025	0.012	0.034
A2	0.022	0.011	0.054	0.044	0.012	<0.001

Without approaching vehicles, the average speed was higher in phases B1, B2, D1, and A2 (Figure 47), and the model confirm a significant positive difference (Table 23). On the contrary, there was a significant difference with a negative coefficient in the first segment after the crossing. These results seem to indicate that when pedestrians confirm that there are no approaching vehicles, they begin to slow down during the road crossing (Phase D2), as upon reaching the other side of the road (phase A1), their speed was lower in comparison to when vehicles were approaching. Conversely, when a vehicle approached or waited, pedestrians increased their speed during the crossing.

The pattern according to the phases without parked vehicles was similar to that without approaching vehicles (Figure 47). Although smaller differences between the speed with or without a parked vehicle exist before the crossing, the contrasts confirm these positive differences.

Before the road crossing (B1 and B2) if there was a parked vehicle, the model results showed that the speed of pedestrians decreases, perhaps due to difficulty of seeing the oncoming vehicles. During the crossing in D2, the pedestrians increased their speed even more if there was a parked vehicle. This behavior could be explained by the pedestrians' desire to get closer to the parked vehicle faster as a way of becoming protected from an approaching vehicle. As previously shown, the difference between having or not parked vehicles was only significant when vehicles were on approach. After the crossing, the speed was lower, and the differences were significant.

Finally, within the characteristics of the infrastructure, there were significant effects of the effective width of the zone, $\hat{\beta}$=-0.013, SE=0.002, p-value 0.001 (wider pedestrian zones were associated with lower speeds), and the distance between the pedestrian crossing and the nearest intersection, $\hat{\beta}$=0.003, SE=0.001, p=0.02 (the greater the distance, the lower the speed of the pedestrians).

4.3.2. Average distance between pair of pedestrians

A sample of 3279 observations of the distance between pairs of pedestrians was analyzed. As explained in section 2.3, the random effects considered for these models were the ID of the pair of participants and the ID of the group of participants.

Table 24 shows summary statistics for the average distance between pairs of pedestrians according to the same variables analyzed the walking speed. Based on these observations (Table 24), it was evident that, on average, the distance between pairs of pedestrians was greater in triads compared to dyads. Similarly, male groups exhibited larger distances compared to female and mixed groups. Furthermore, the distance between pedestrians increased during the crossing phase compared to the pre-crossing phase.

Table 24 – Descriptive statistics of the distance between pairs of pedestrians.

Group of factors	Variable (Abbreviation)	Levels		Distance between pair of pedestrians (m)			
				Min	Max	Mean	SD
Social factors	Size group (Size)	2		0.427	2.129	0.813	0.192
		3		0.376	2.254	0.866	0.258
	Sex composition of the group of participants (Sex)	Female		0.388	2.101	0.840	0.226
		Male		0.431	2.254	0.894	0.260
		Mix		0.376	2.237	0.838	0.242
External factors	Study site (Site)	S1		0.376	1.729	0.821	0.204
		S2		0.430	2.129	0.852	0.258
		S3		0.385	2.254	0.884	0.261
	Crossing phase (Phase)	Before	B1	0.413	1.699	0.787	0.210
			B2	0.425	2.047	0.860	0.242
		During	D1	0.477	2.251	0.902	0.234
			D2	0.475	2.237	0.862	0.220
		After	A1	0.376	2.254	0.852	0.265
			A2	0.385	2.114	0.852	0.271
	Approaching vehicles (Veh)	Yes		0.376	2.129	0.854	0.242
		No		0.385	2.254	0.849	0.247
	Interaction with other pedestrians (Ped)	Yes		0.413	1.785	0.864	0.244
		No		0.376	2.254	0.850	0.244
	Presence of parked vehicles (Parked)	Yes		0.385	1.872	0.838	0.244
		No		0.376	2.254	0.858	0.244

As with the pedestrians' walking speed, the model was fitted using LMMs. The final model contains all significant predictor variables (Equation 4).

For $i = 1, \dots, 5; j = 1, \dots, 18; k = 1, \dots, mij$, the model, can be written as:

$$D_{ijk} = \beta_O + Size_{ijk} \times Sex_{ijk} + Size_{ijk} \times Park_{kij} + Phase_{ijk} + Veh_{ijk} + \alpha Width_{ijk} + u_{ij} + b_i + \varepsilon_{ijk} \quad (4)$$

Satterthwaite's test was used to identify variables with significant influence on the average distance between pedestrians, and the interactions. The results are presented in Table 25. The non-significant social factor was *D_Leg* (legs length) and external factors were: *Site* (study site), *Pav* (pavement), *W_Lanes* (lane width), *L_Crosswalk* (crosswalk length), *Dist* (Distance from the crosswalk to the nearest intersection), *and Ped* (interaction with other pedestrians).

Table 25 – Satterthwaite's test results for the model of the average distance between pairs of pedestrians.

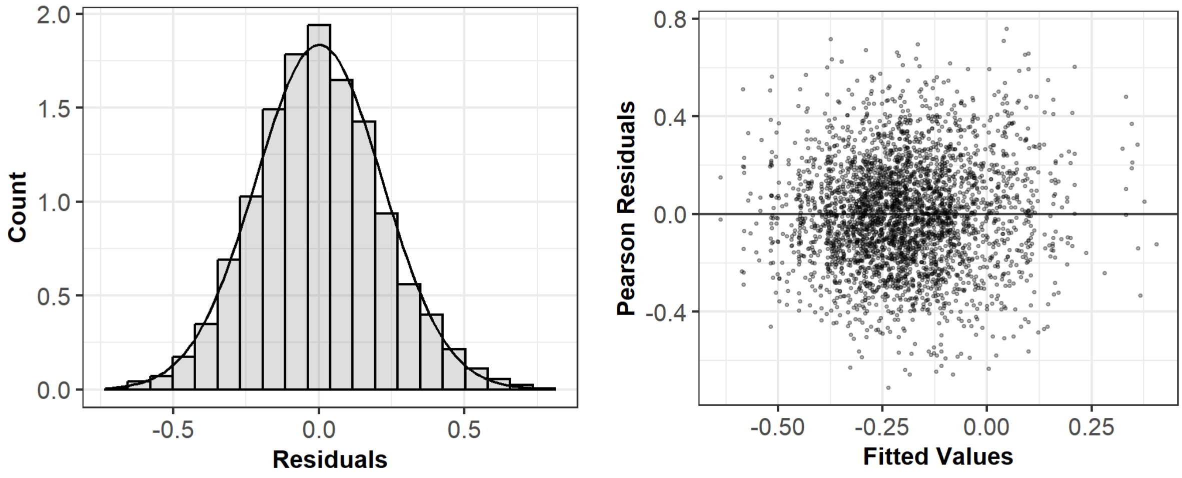
Variable	**Sum Sq**	**Num DF**	**F value**	**p-value**
Sex	0.473	2.000	4.870	0.010
Size	1.175	1.000	24.178	0.000
Phase	6.161	5.000	25.353	<0.001
Veh	0.383	1.000	7.888	0.005
Parked	0.202	1.000	4.151	0.042
Width	0.490	1.000	10.073	0.002
Sex × Size	0.400	2.000	4.113	0.016
Size × Parked	0.299	1.000	6.142	0.013

Full summary statistics of the model are presented in Table 26. Contrasts were used to analyze the interactions between variables and to summarize the model results according to each variable.

Table 26 – Linear mixed model result of distance between pair of pedestrians.

Variable	**Value of category**	**'Distance' model (n =3279)**		
		Estimate	**SE**	**p-value**
Group size	Size_2		Reference	
	Size_3	0.077	0.023	0.001*
Group sex	Sex_Female		Reference	
	Sex_Male	0.144	0.045	0.002*
	Sex_Mix	0.088	0.037	0.020*
Crossing phase	Phase_B1		Reference	
	Phase_B2	0.085	0.013	<0.001*
	Phase_D1	0.155	0.014	<0.001*
	Phase_D2	0.122	0.015	<0.001*
	Phase_A1	0.071	0.013	<0.001*
	Phase_A2	0.067	0.013	<0.001*
Approaching vehicles	Veh_No		Reference	
	Veh_Yes	0.029	0.010	0.005*
Parked vehicles	Parked_No		Reference	
	Parked_Yes	-0.050	0.019	0.009*
Effective width	Width_E	-0.010	0.003	0.002*
Group sex × Group Size	Sex_Female:Size_2		Reference	
	Sex_Male:Size_3	-0.051	0.031	0.098
	Sex_Mix:Size_3	-0.075	0.026	0.004*
Group Size × Parked Vehicles	Size_2:Parked_No		Reference	
	Size_3:Parked_Yes	0.053	0.022	0.013*
ICC1			0.133	
ICC2			0.316	
AIC			-329.400	

Based on the diagnostic plot for the model described in Equation (4), the histogram of the residuals suggests normality (Figure 48 (a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 48 (b)). The residuals appear to be homogeneously distributed.



(a) (b)

Figure 48. Diagnostic plots - residuals for the model (average distance): (a) Histogram of the residuals; (b) Pearson residual versus fitted values.

One variable that did not exhibit a significant influence on distance between pedestrians was the study site. This can be visually verified in Figure 49, where no substantial variations are observed depending on the site. Contrasts were utilized to analyze the significant interactions among variables and to compare the levels within each variable. The obtained results were categorized into social and external factors.

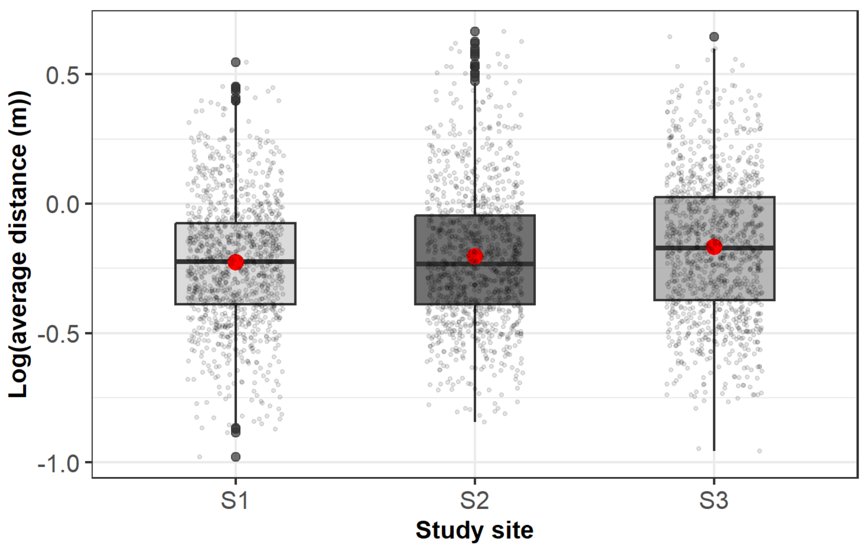


Figure 49. Boxplot of distance between pairs of pedestrians as a function of study site.

4.3.2.1. Social factors

The interactions between group size and sex were statistically significant. As illustrated in Figure 50, distances between pedestrians were greater for triads than for dyads. The variation was 10% for all-female, 7% for all-male, and 4% for mixed groups.

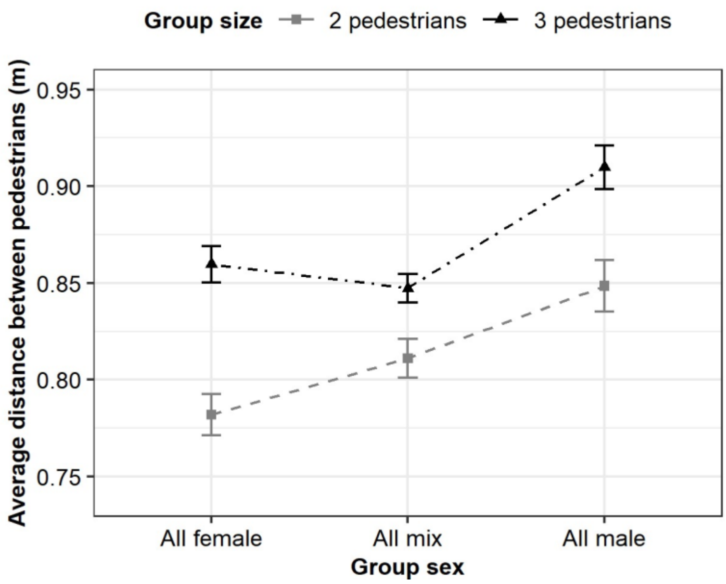


Figure 50. Average distance between pairs of pedestrians and respective standard error according to the group size per group sex.

Contrasts were utilized to analyze the effect of the interaction between sex composition *(Sex)* and group size *(Size)* on the distance between pedestrians. When comparing groups of dyads and triads based on sex, significant differences were observed in male groups ($\hat{\beta}$=-0.053, SE=0.022 p=0.016) and female groups ($\hat{\beta}$=-0.104, SE =0.024, p-value <0.001), but not in mixed groups ($\hat{\beta}$=-0.017, SE=0.014, p=0.056).

Furthermore, male pairs appear to maintain a greater distance between them compared to mixed or female pairs. The contrasts for the interaction between sex and size revealed a significant difference between males and females for dyads and triads. There was only a difference between male and mixed groups for triads, as shown in Table 27.

Table 27 – Contrasts of the group size per group sex.

Sex	Size					
	2 pedestrians			3 pedestrians		
	Estimate	SE	p-value	Estimate	SE	p-value
Female - Male	-0.144	0.046	0.005	-0.093	0.038	0.043
Female - Mix	-0.088	0.038	0.056	-0.012	0.031	0.919
Male - Mix	0.057	0.038	0.294	0.081	0.032	0.032

Interactions of group size *(Size)* with parked vehicles *(Parked)* were also significant for the distance between pedestrians. As already mentioned, the distance is greater when the size of the group increases. However, Figure 51 shows that without parked vehicles, the distance was greater than with parked vehicles, particularly for groups of two pedestrians. The contrast confirms these positive differences. ($\hat{\beta}$=0.050, SE=0.019, p=0.009). The differences in triads were not significant ($\hat{\beta}$=-0.004, SE=0.011, p=0.745).

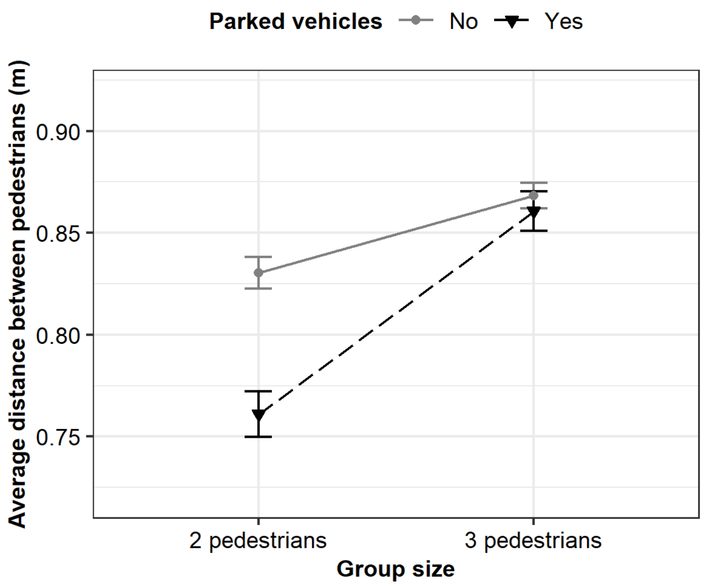


Figure 51. Average distance between pairs of pedestrians and respective standard error according to the presence of parked vehicles per group size.

4.3.2.2. External factors

Regarding external factors, the effective width of the zone *(Width)* ($\hat{\beta}$=-0.010, SE =0.003, p=0.002) had a significant effect on the average distance. The distance between pedestrians decreases with wider pedestrian zones (Figure 52). These results are contrary to what was expected. With less space, shorter distances between people were the expectation.

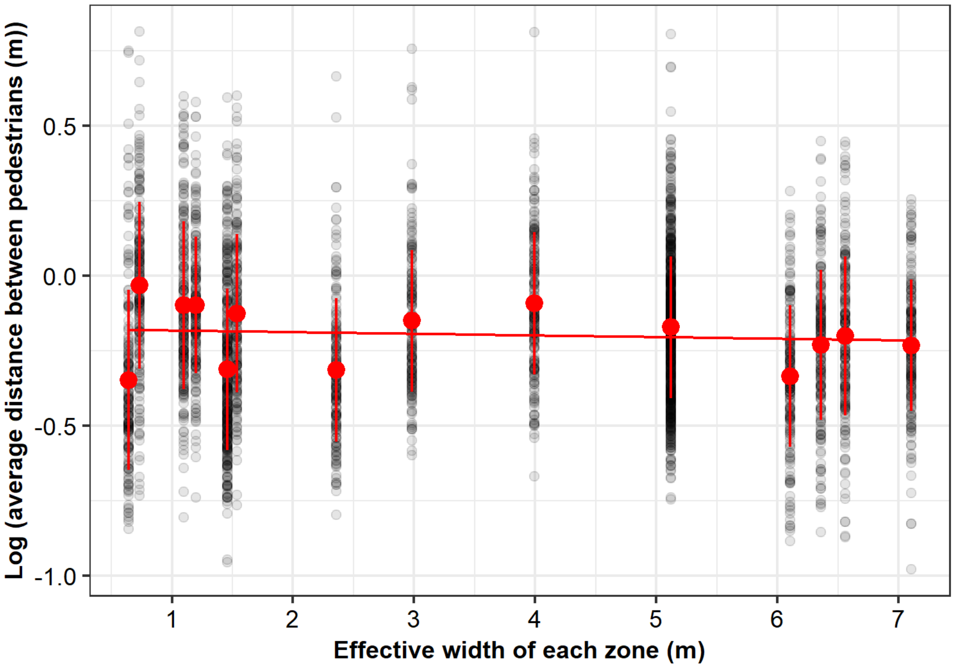


Figure 52. Distance between pairs of pedestrians as a function of the effective width of each zone (sidewalk and crosswalk).

Furthermore, the distance between pedestrians depends on the crossing phase (Figure 53). Near the crosswalk (B2) the distance increases and the differences between the segments (B1 and B2) before the road crossing were significant ($\hat{\beta}$=-0.085, SE=0.013, p-value <0.001). In addition, the distance between pedestrians was greater when a vehicle approached *(Veh)* ($\hat{\beta}$=0.029, SE=0.010, p=0.005). This could indicate differences in the decision-making process to cross, which would increase the distance if one of the people in the pair decides to cross first.

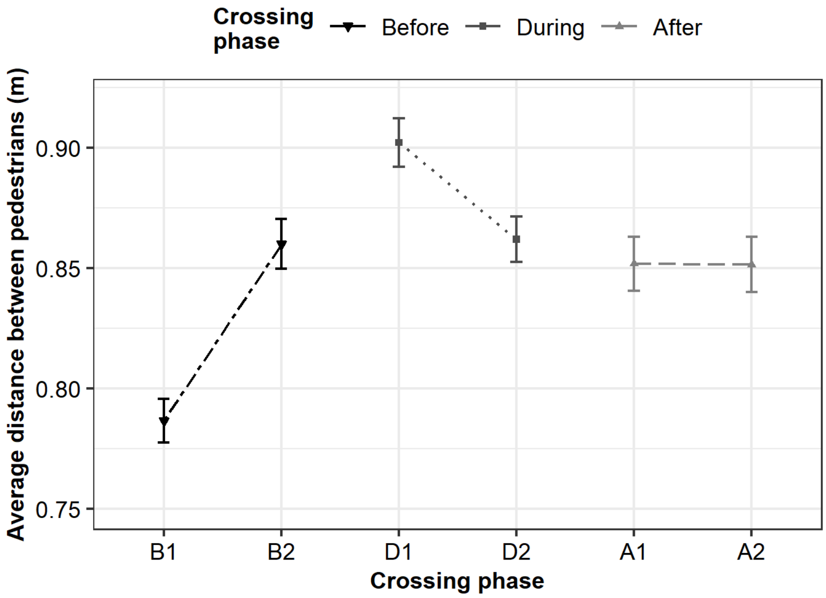


Figure 53. Average distance between pedestrians by crossing phase.

Between the segment during (D1-D2) and after (A1-A2) the crossing there were no significant differences ($\hat{\beta}$=-0.033, SE=0.014, p=0.168 and $\hat{\beta}$=-0.005, SE=0.013, p=0.999). During the first segment of the road crossing (D1) the average distance increased, and the difference between the previous segment (B2) was significant ($\hat{\beta}$=-0.069, SE=0.014, p-value <0.001).

Then, in the second segment during the crossing (D2) the average distance decreased and the difference with the next segment (A1) was significant ($\hat{\beta}$=0.050, SE=0.015, p=0.012). This could reinforce the fact that at the moment they have to choose to cross the street and assess the approaching vehicle, the pedestrians tend to separate but eventually join again near the end of the crossing.

4.3.3. Average angle of pedestrians

A total of 3412 observations of the average angles of pedestrians were included in the analysis. The models accounted for random effects by considering the ID of the pair of participants, as depicted in Figure 54.

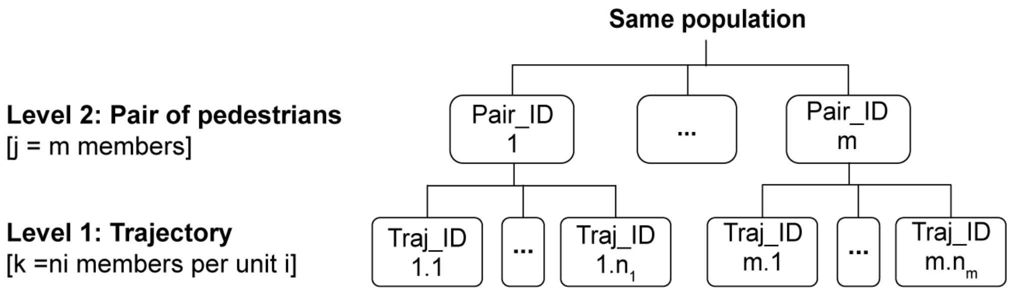


Figure 54. Multilevel diagram model of pedestrians' angles.

In the analysis of pedestrian's angles, it was necessary to include a subdivision based on the group size. The pair of dyads was referred to as pair A, and in the case of triads, the first pair was referred to as pair B, and the second pair as pair C (Figure 55).

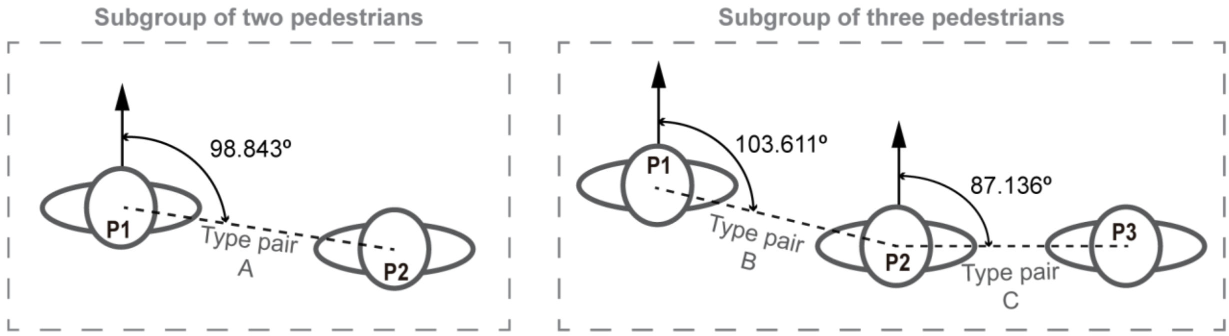


Figure 55. Type of pedestrians pairs according to the group size with the corresponding average angles.

Table 28 shows the summary statistics for the average angles of pedestrians according to the same variables analyzed for the walking speed. On average, the angles of the pairs of pedestrians were greater for the following conditions: in triads, for type of pair B than A and C pairs, in mixed groups (compared to female and male), after crossing (compared to before and during), without approaching vehicles, with interaction with out-group pedestrians and with presence of parked vehicles.

Table 28 – Descriptive statistics of the pedestrians' angles.

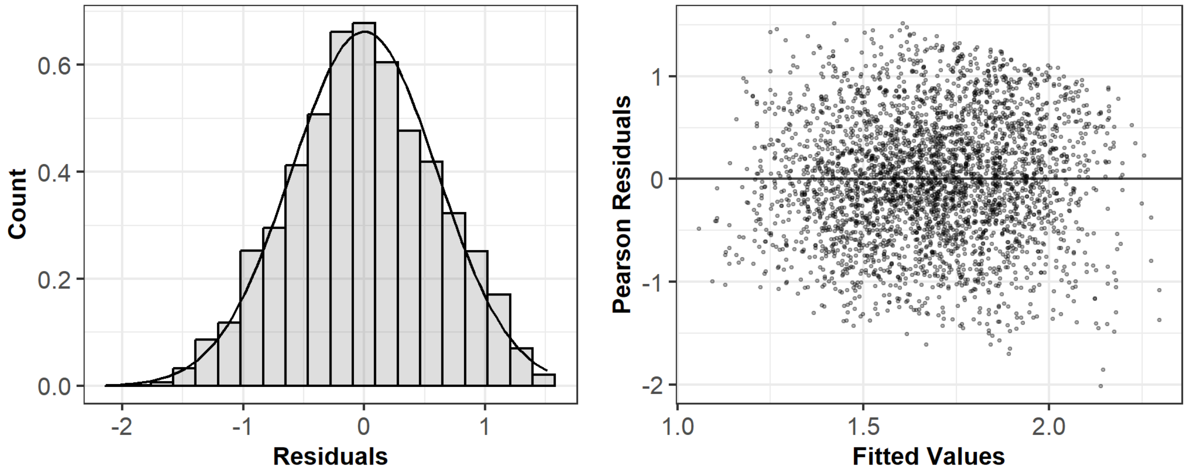
Group of factors	Variable (Abbreviation)	Levels		Angles between pair of pedestrians (º) Min	Max	Mean	SD
Social factors	Size group (Size)	2 (Pair A)		16.437	177.847	98.843	29.633
		3 (Pair B)		2.687	178.337	103.611	37.432
		3 (Pair C)		3.485	178.741	87.136	40.831
	Sex composition of the group of participants (Sex)	Female		2.687	178.337	95.560	36.507
		Male		5.767	177.106	95.419	38.930
		Mix		3.852	178.741	97.518	37.499
External factors	Study site (Site)	S1		2.687	176.568	88.768	34.687
		S2		9.014	178.741	98.820	36.509
		S3		3.485	178.337	101.721	39.963
	Crossing phase (Phase)	Before	B1	2.687	178.337	87.153	40.635
			B2	4.605	173.427	89.215	35.299
		During	D1	23.062	174.113	93.103	28.618
			D2	19.319	178.741	98.818	27.430
		After	A1	7.192	177.811	104.544	37.852
			A2	3.485	177.847	107.230	48.590
	Approaching vehicles (Veh)	Yes		2.687	178.741	95.232	37.738
		No		3.485	178.337	99.270	37.050
	Interaction with other pedestrians (Ped)	Yes		2.687	178.337	97.160	37.245
		No		4.605	178.741	92.463	39.204
	Presence of parked vehicles (Parked)	Yes		9.014	178.741	101.106	37.778
		No		2.687	177.825	94.652	37.334

As with the pedestrians' walking speed, the model was fitted using LMMs. The final model contains all significant predictor variables (Equation 5).

For $j = 1, \dots, 18; k = 1, \dots, mj$, the model, can be written as:

$$A_{jk} = \beta_O + Type\_Pair_{jk} + Site_{jk} + Phase_{jk} + Park_{jk} + Ped_{jk} + u_j + \varepsilon_{jk} \qquad (5)$$

Based on the diagnostic plot for the model described in Equation (5), the histogram of the residuals suggests normality (Figure 56 (a)). Any systematic increase or decrease in the variance of residuals was verified (Figure 56 (b)). The residuals appear to be homogeneously distributed.



(a) (b)

Figure 56. Diagnostic plots - residuals for the model (average angles): (a) Pearson residual versus fitted values; (b) Histogram of the residuals.

Satterthwaite's test was used to identify variables with significant influence on the average angles of pedestrians, and the interactions. The results are presented in Table 29.

Table 29 – Satterthwaite's test results for the model of the average angle of pedestrians.

Variable	**Sum Sq**	**Num DF**	**F value**	**p-value**
Type of pair	47.346	2	64.2081	<0.001
Phase	49.936	5	27.0883	<0.001
Parked	12.61	1	34.2022	<0.001
Ped	2.027	1	5.4973	0.009
Site	12.672	2	17.1845	<0.001

The non-significant social factor was *D_Leg* (legs length) and external factors were *Width* (effective width of each zone), *Veh* (approaching vehicles), *Pav* (pavement), *W_Lanes* (lane width), *L_Crosswalk* (crosswalk length), and *Dist* (Distance from the crosswalk to the nearest intersection).

Full summary statistics of the model are presented in Table 30. Contrasts were used to analyze the interactions between variables and to summarize the model results according to each variable.

Table 30 – Linear mixed models result of average angles of pedestrians.

Variable	Value of category	'Angle' model (n =3412)		
		Estimate	**SE**	**p-value**
Type of pair	Type_A		Reference	
	Type_B	0.062	0.029	0.032
	Type_C	-0.205	0.029	0.000
Study site	Site_S1		Reference	
	Site_S2	0.169	0.040	0.000
	Site_S3	0.222	0.039	0.000
Crossing phase	Phase_B1		Reference	
	Phase_B2	0.048	0.036	0.180
	Phase_D1	0.097	0.036	0.007
	Phase_D2	0.205	0.036	0.000
	Phase_A1	0.296	0.036	0.000
	Phase_A2	0.318	0.036	<0.001
Parked vehicles	Parked_No		Reference	
	Parked_Yes	0.147	0.025	0.000
Out-group pedestrians	Ped_No		Reference	
	Ped_Yes	-0.073	0.031	0.019
ICC1			0.035	
AIC			6382.5	

4.3.3.1. Social factors

The type of pair of pedestrians had a statistically significant effect on the average angle. As shown in Figure 57, pedestrians' angles were greater for type B pairs (triads) compared to type C pairs (triads) and type A pairs (dyads). Additionally, it can be observed in the figure that there is less variation in angles for type A compared to types B and C.

On the one hand, based on the contrast results, the difference in average angles between type A and type B pairs was not statistically significant ($\hat{\beta}$=-0.062, SE=0.029, p=0.085). On the other hand, the difference between type C pairs and type A pairs was significant ($\hat{\beta}$=-0.205, SE=0.029, p=<0.001), as was the difference between type C pairs and type B pairs ($\hat{\beta}$=-0.267, SE=0.024, p=<0.001).

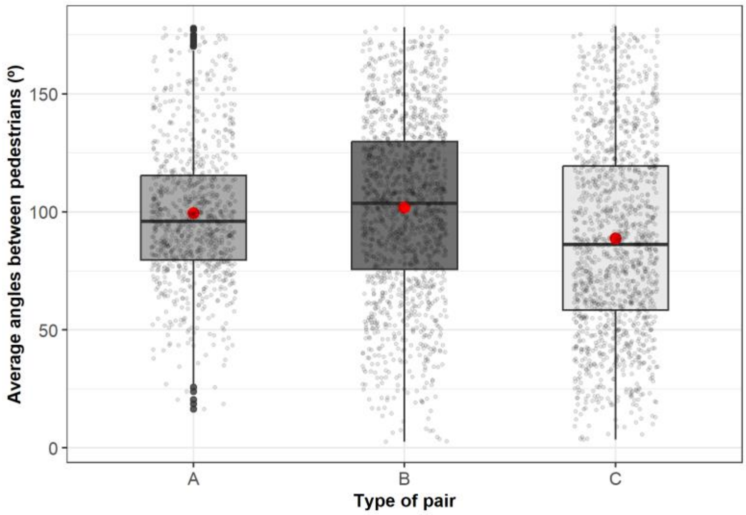


Figure 57. Boxplot of angle of pedestrians as a function of type of pair.

4.3.3.1. External factors

Regarding external factors, unlike speed and distance between pairs of pedestrians, the differences vary according to the study site, as shown in Figure 58. Significant differences were found in the mean angles between individuals between S1 and S2 ($\hat{\beta}$=-0.169, SE=0.0406, p=<0.001) and between S1 and S3 ($\hat{\beta}$=-0.222, SE=0.0402, p=<0.001). No significant differences were found between S2 and S3 ($\hat{\beta}$=-0.053, SE=0.0400, p=0.391).

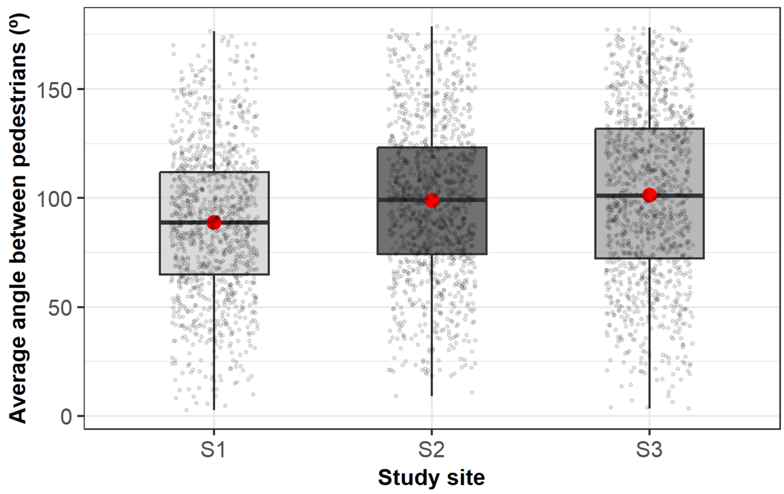


Figure 58. Boxplot of angle of pedestrians’ pairs as a function of study site.

Although each zone's effective width was insignificant, as depicted in Figure 59, the average angles of pedestrians decreases as the effective width of the walking areas, such as sidewalks and crosswalks, increases. Therefore, the previous result could have been influenced by the available space for walking. In this case, the study site S1 represents a street with wider sidewalks. Unlike S2 and S3, the sidewalks are narrower, and there is a slight variation in width between those two.

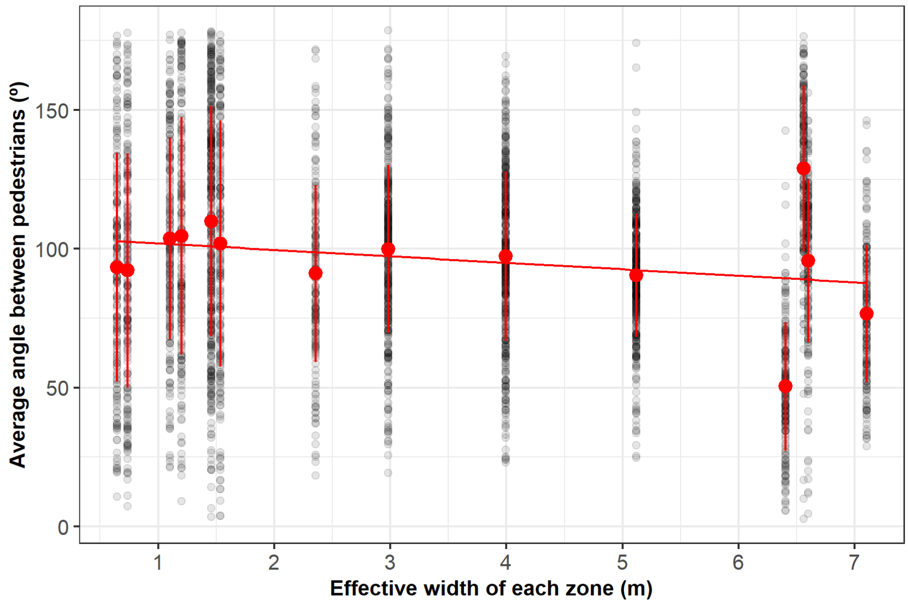


Figure 59. Average angles of pedestrians' pairs as a function of the effective width of each zone (sidewalk and crosswalk).

In addition, the angles of pedestrians also vary according to the crossing phase, as depicted in Figure 60.

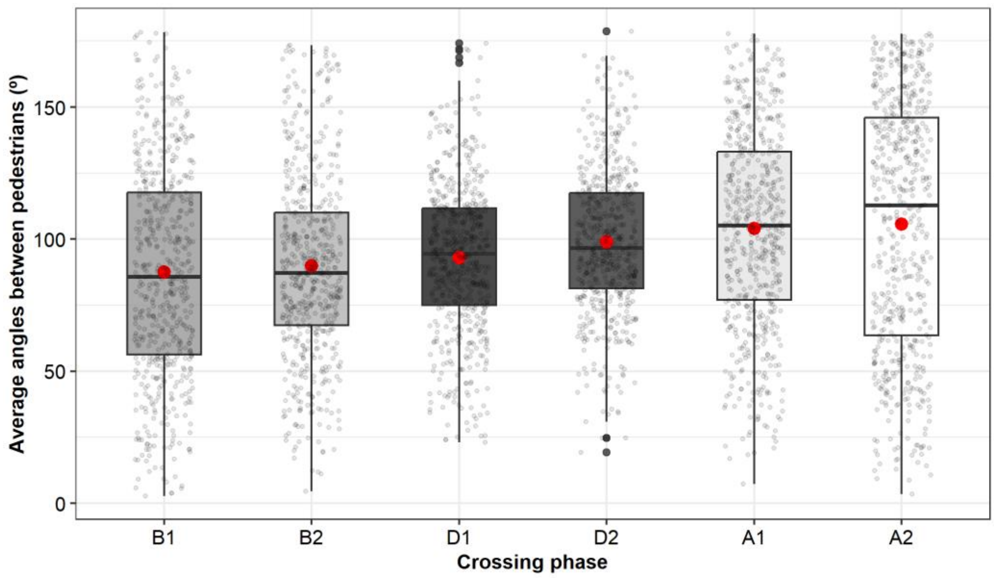


Figure 60. Boxplot of average angles of pedestrians' pairs as a function of crossing phase.

The average angle increases as people cross the street. However, there is less variation in angles in the segment closest to the crossing (B2) and in the segments during the road crossing (D1 and D2). According to the results of the model and the contrasts presented in Table 31, there is a significant difference (p-value < 0.05) between the two segments during the crossing phase, with the average angle being higher in D2. Similarly, there is a significant difference between the initial average angle (B1) and the final average angle (A2), with the final angle being greater.

Table 31 – Contrasts results of the crossing phase.

Crossing phase	**Estimate**	**SE**	**p-value**
B1 - B2	-0.057	0.036	0.609
B2 - D1	-0.079	0.037	0.269
D1 - D2	-0.108	0.036	0.035
D2 - A1	-0.060	0.037	0.577
A1 - A2	-0.013	0.036	0.999
B1 - A2	-0.318	0.036	<.0001

The angles between pairs of pedestrians were also affected by the presence of interactions with pedestrians outside their group. As can be observed in Figure 61, when interactions occur, the angle decreases, and according to the results of the model, this difference is significant ($\hat{\beta}$=-0.082, SE=0.031 p=0.009).

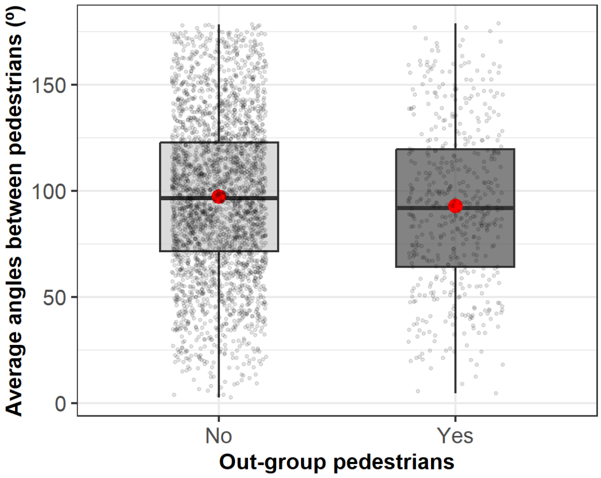


Figure 61. Boxplot of average angle of pedestrian pairs as a function of interaction with out-group pedestrians.

Lastly, when there were parked cars, the average angle of pedestrians increased, as can be observed in Figure 62. According to the results of the model, this difference is significant ($\hat{\beta}$=0.145, SE=0.025 p=<0.001).

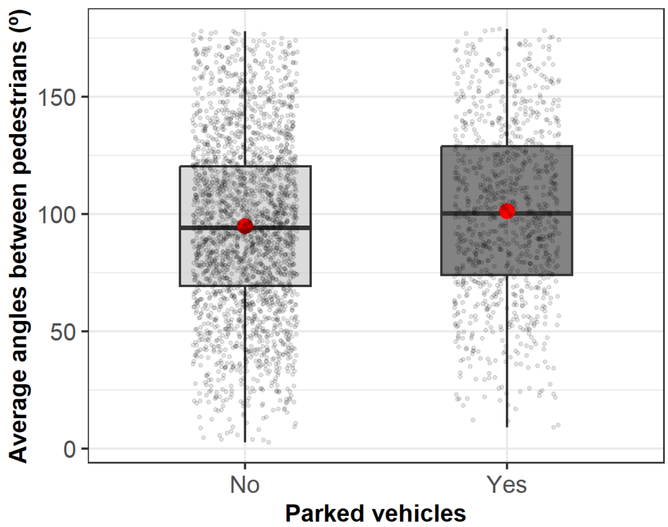


Figure 62. Boxplot of angle of pedestrians as a function to the presence of parked vehicles.

4.4. Discussion

The findings reported in this chapter highlight the dependence of walking behavior of social group pedestrians on group size and the composition by sex also in the road crossing context under normal conditions of low pedestrian density.

Size

An increase in group size was found to be associated with a decrease in average speed and an increase in average distance between pairs of pedestrians. Previous studies have shown that in areas without vehicle interactions, such as commercial areas, streets, or inside universities, social groups walk at a slower speed than isolated pedestrians (Federici et al., 2014; Gorrini et al., 2014; Moussaïd et al., 2010). The decrease in speed by the groups was attributed to the need to maintain cohesion between individuals to facilitate social interactions (Gorrini et al., 2014; Moussaïd et al., 2010). However, these studies were conducted under medium to high pedestrian densities, and the decrease in speed could be an effect of the group's difficulty to stay together. Similarly, it was found in the present study that pedestrian groups also walked at a lower speed under low-density conditions, even while crossing the street.

With regard to the distance between pedestrians, the largest distances were observed among triads compared to dyads (Moussaïd et al., 2010; Willis et al., 2004). This could be explained by a tendency for greater intimacy among couples among triplets (Willis et al., 2004). Nevertheless, it is also possible that triads organize themselves differently to facilitate communication. For instance, on sidewalks, where there is limited space, they may need to adopt different formations, such as a "V"-like shape observed by Moussaïd et al. (2010), where the distances between people are greater.

Table 32 presents the average distances between individuals in this study, as well as in previous studies where Moussaïd et al. (2010) analyzed distances on sidewalks and L. Fu et al. (2019) analyzed distances on stairs. These results indicate that under low-density conditions, the typical interpersonal distance ranges from approximately 0.80 m to 0.90 m. However, in this study, relatively greater distances between individuals were observed. It is worth noting that this study includes an analysis of crossing phases in addition to pedestrian distances on sidewalks. Therefore, these differences in distance could potentially be attributed to variations in the crossing phases, which will be further discussed later.

Table 32 – Average distance between pedestrians for each group size.

Group size	Pair	(Moussaïd et al., 2010)				(L. Fu et al., 2019)		In this study	
		Low density		**Moderate density**		**Stairs**		**Low density**	
		D (m)	**SE**	**D (m)**	**SE**	**D (m)**	**SE**	**D (m)**	**SE**
Dyads	P1 - P2	0.78	0.02	0.54	0.01	0.78	0.03	0.81	0.01
Triads	P1 - P2	0.79	0.05	0.55	0.01	0.77	0.04	0.86	0.01
	P2 - P3	0.81	0.10	0.62	0.04	0.80	0.04	0.87	0.01

To analyze the average angles of pedestrians' pairs, in addition to group size, it was necessary to classify them into different types: Type A for groups of 2 people, Type B (p1-p2), and Type C (p2-p3) for groups of 3 people. The results showed no significant differences in the average angle of pedestrian pairs in dyads (Type A) and the first pair (Type B) in triads. However, the average angle of the second pair in triads (Type C) was significantly smaller than the other two types (Type A and Type B). This supports previous findings that indicate a tendency for individuals in groups of 3 to adopt a "V"-like shape while walking, as previously mentioned even in studies on stairs.

Nevertheless, as shown in Table 33, in this study, the angles between P1 and P2 in both dyads and triads were larger. Furthermore, there are relatively greater differences compared to the angles reported by Fu et al. (2019). It is crucial to note that this study considered different crossing phases, not just when pedestrians walk in the same direction on sidewalks or stairs. With the results, it was possible to observe that the spatial organization of the pedestrians varies through the crossing phases, but these results will be discussed later.

Table 33 – Average angles between pedestrians for each group size.

Group size	Pair	(Moussaïd et al., 2010)				(L. Fu et al., 2019)		In this study	
		Low density		**Moderate density**		**Stairs**		**Low density**	
		A (º)	**SE**	**A (º)**	**SE**	**A (º)**	**SE**	**A (º)**	**SE**
Dyads	P1 - P2	89.8	1.12	90.3	0.8	80.22	2.51	98.84	1.01
Triads	P1 - P2	97.8	5.14	107.9	2.84	90.61	4.26	103.61	1.04
	P2 - P3	87.1	4.46	70.6	2.55	73.29	4.81	87.14	1.13

Sex

The average speed and distance were also found to be affected by the sex composition of the groups, unlike the average angles where no significant effect was observed due to the sex composition. Firstly, a clear difference in average speed was observed between male groups and female/mixed groups before and after the road crossing, with male groups showing higher speed. These findings were expected, as males are generally associated with higher average speeds than females (Montufar et al., 2007), and other studies have shown that male groups walk faster than females and mixed groups (Costa, 2010; Willis et al., 2004). Costa (2010) suggested that the deeper the affective involvement between a couple (mixed dyads), the slower the walking speed tends to be. In this study, the participants were friends, and little difference was found between the walking speed of female and mixed dyads (except before the road crossing).

In contrast, Federici et al. (2014) did not observe differences in walking speed according to the sex of the group. However, the analysis conditions of these two works were different, as Costa (2010) observed the group behavior of pedestrians while walking on sidewalks and in pedestrian areas in different urban settings, while Federici et al. (2014) focused on investigating pedestrian dynamics in medium-high density situations with observations of incoming pedestrian flows to a university admission test. This difference could indicate that in normal or/and low-density conditions, sex can be a relevant factor in the speed of pedestrians.

Secondly, male groups maintained a greater distance than the female groups (dyads and triads), as well as the mixed triads. No difference was observed between female and mixed groups. Similar results were reported by Costa (2010), who found that male dyads and triads tended to walk together less often than female dyads, and mixed dyads walked together more often than same-sex dyads. This is consistent with the literature on the topic of interpersonal distance, which indicates that female pairs tend to maintain closer distances than male pairs, possibly due to a greater predisposition of women to be affiliative (see Uzzell & Horne (2006) for a review and discussion).

Phases

It was found that neither the pedestrians' average speed nor the distance or the angles between pairs remained constant throughout the three crossing phases, according to the results. Empirical observations in previous studies of stairs inside a university had shown that the average distance for groups of different sizes is stable for the purpose of maintaining group structure (L. Fu et al., 2019). However, the results of this study showed that the distance between pairs of pedestrians changed according to the phases of the road crossing. One possible reason for this may be that individuals increase their distance from each other (separate) near the crosswalk when deciding whether to cross or not. Furthermore, since the width of the crosswalk is usually greater than the effective width of the sidewalks, the distance between pedestrians could also be expected to increase during the road crossing. However, in this study, the effect of the effective width showed that the distance was smaller in the broader zones.

It was observed that the average angles of pedestrians were significantly lower at study site S1, where the sidewalks were the widest. This observation suggests that if there is enough space to walk side by side, pedestrians prefer to be more aligned (close to a 90° angle). For example, during the crossing phase, typically characterized by the broadest and least obstructed area, there was less angle variation than in other phases. This implies that walking directly in front of each other (at an angle close to 180°), as might be necessary on narrow sidewalks due to limited space, was not observed. However, it was noted that the angle at the beginning of the trajectory was significantly smaller than at the end, indicating that the angle varied according to the crossing phases. This suggests that the crossing phases influenced the angle variation, which may be directly related to the interaction with the externalfactors, such as obstacles or other pedestrians outside the group.

With regards to the average speed, there was a significant reduction before the road crossing, followed by an increase during the crossing and a posterior reduction back to the initial speed. This pattern was expected since before the crossing in segment B2, near the crosswalk, pedestrians evaluate whether they can cross or not, and while making that judgment, they reduce their speed. During road crossings, an increase in speed was also expected since previous studies have reported that pedestrian speeds are higher when crossing streets than on sidewalks (although the behavior of social groups has not been previously analyzed (Ishaque & Noland, 2008).

An important conclusion of this study is that the average speed pattern is maintained through the phases by group size (higher speed for singles and lower for groups in all phases). However, there were some differences in the pattern throughout the phases according to the groups' sex. Before the road crossing, the speed reduction was higher for female groups, followed by mixed and male groups. It was the only phase where there was a significant difference between females and mixed groups. Although the objective of this study was not to analyze the effect of sex on the decision-making process to cross, the observed differences may indicate that sex plays an important role when pedestrians decide to cross. Also, the effect of oncoming vehicles was significant on average speed by sex composition but not by group size.

This observation is consistent with those of Holland and Hill (Holland & Hill, 2007). They compared the intention to cross and the perceived risk through the answers to a questionnaire in which people were asked to evaluate whether to cross or not in hypothetical textual risk descriptions, concluding that women were less likely than men to try to cross under risky situations. Also, Díaz (2002) analyzed the attitude toward (illegal) mid-block crossing and found that men reported more violations than women.

Unlike before and after the crossing, during the road crossing, there was no significant difference in average speed between the group sex composition. This could indicate that the behavioral approach was different between phases. During the crossing, the objective of reaching the other side as quickly as possible may override the behavioral characteristics on the sidewalks. The greater the risk involved in walking, the higher the walking speed (Ishaque & Noland, 2008). This contrasts the conclusion of Montufar et al. (Montufar et al., 2007), who found significant differences between the speed of men compared to women during street crossings, although they did not study the behavior of pedestrians in groups.

Interactions with parked vehicles and out-group pedestrians

The results revealed that the presence of parked vehicles had an effect according to the phase. If there was a parked vehicle before the road crossing, the pedestrians' average speed decreased. Oppositely, during the crossing, pedestrians increased their speed even more. These results may align with the conclusions of previous studies, which analyzed the acceptance of the gap for mid-block street crossings and red-light violations. On the one hand, the presence of illegal parking seems to discourage pedestrians from crossing because it affects pedestrians' visibility, forcing pedestrians to be more careful and reject shorter time gaps for crossing, according to Yannis et al. (2013). This could be related to the decreased speed before crossing.

On the other hand, according to Dommes et al. (2015) the presence of parked vehicles generated red light violations, suggesting that parked vehicles may increase the pedestrians' feeling of safety once the road width decreases. This could be related to increased speed during the crossing once the decision to cross has been taken.

In addition, the presence of parked vehicles also significantly affected the average angle and distance between pedestrians. When there were parked vehicles, the distance and angles decreased. This suggests that, similar to the speed findings, pedestrians tend to get closer to each other due to the difficulty of seeing approaching vehicles, and they make a collective decision to advance when they deem appropriate.

Finally, the results show that, in conditions of low pedestrian density, the differences in average speed due to interaction with other pedestrians were significant for triads and groups of women. Groups of pedestrians slow down, perhaps to avoid splitting up. No significant differences were found in the average distance between pedestrians. However, there was an effect on the average angle of pedestrian pairs. When interactions occurred with pedestrians outside the group, the angle experienced a slight increase. This suggests that pedestrians adjust their speed in typical situations, and the spatial organization remains relatively unchanged. Nevertheless, this effect may primarily impact triads due to the larger space they occupy, which encourages them to avoid separating from one another.

4.5. Conclusions

Even though it had been revealed in previous studies that pedestrian traffic is comprised of groups and that social interactions are crucial for organizing human crowds, little or no research had been conducted on the behavior of pedestrians' social groups under normal conditions near pedestrian crossing sites.

The findings suggest several critical factors in the movement preferences of social groups, even under normal conditions and in places with low pedestrian density. It was found that typical walking patterns arose from local interactions between group members. Differences in speed, distance and angles between young pedestrians depended on social factors (group size and sex composition) and external factors (crossing phases and interaction with other pedestrians, approaching and parked vehicles).

The results of this study should help to increase understanding of how young pedestrians in social groups interact with each other and with the environment, thus improving the way scientists, engineers, policymakers, and designers increase the safety of vulnerable road users. The description of several fundamental elements of movement behavior (speed, distance and angles) can be used to assign realistic values to models of pedestrian behavior based on parameters such as group size, sex composition, and crossing phases.

Furthermore, these findings could be used in risk studies of vehicle-pedestrian interactions and in new challenges concerning pedestrian dynamics, for example, to create rules and improve shared space areas, as well as to give indications to improve the automatic detection of pedestrians by autonomous vehicles.

CHAPTER 5

ANALYSIS OF PEDESTRIANS' ROAD CROSSING BEHAVIOR, IN SOCIAL GROUPS OF DIFFERENT CULTURES

5.1. Introduction

Pedestrian behavior is influenced by various factors at personal, external, social, and cultural levels. To accurately predict pedestrian behavior, it is essential to consider these factors together (Arellana et al., 2020; Moussaïd et al., 2010; Papadimitriou et al., 2010).

According to Hofstede's (1980) theory, individuals have stable mental programming that makes their behavior in parallel situations similar. This programming can be categorized into three levels: individual, collective, and universal. While all humans share the universal level, the collective level is specific to certain groups or categories, and the individual level pertains to unique personality traits.

Personal factors on an individual level have been extensively studied, but it is also essential to consider the influence of social and cultural factors. Specifically, the specific collective level refers to the social information used by pedestrians based on the behavior of people in a given situation (social factors) (Faria et al., 2010; Moussaïd et al., 2010). In contrast, the general collective level of influence on pedestrian behavior refers to the ecological context in which individuals exist (cultural factors) (Nordfjærn et al., 2014; Pelé et al., 2017; Sorokowska et al., 2017).

Previous studies have emphasized the significance of cultural and location-specific factors in shaping pedestrian behavior, emphasizing the need to investigate pedestrian behavior in diverse socioeconomic contexts. Developing effective interventions and road safety policies requires understanding the specific context rather than generalizing results from local studies (Bosina & Weidmann, 2017; Nordfjærn et al., 2014; Pelé et al., 2017; Sueur et al., 2013).

However, most of these studies have focused on analyzing how culture affects risk perception across different countries(Nordfjærn & Şimşekoğlu, 2013; Pelé et al., 2017; Sueur et al., 2013). Some studies have examined operational variables like average walking speed across countries (Bosina & Weidmann, 2017) without considering the effect of social interactions. Similarly, other studies have explored how individuals from different cultures differ in their preferences for interpersonal distance in various social contexts, but they have considered crossing phases (Sorokowska et al., 2017). Therefore, further research is needed to understand how cultural and social factors influence pedestrian behavior during street crossings.

This chapter are studied potential differences in pedestrian behavior influenced by cultural factors on two streets in Colombia and Portugal. Additionally, it will examine the impact of social influence on individual behavior by comparing the behavior of pedestrians when walking alone versus in groups during street crossings.

In contrast to previous research, this study takes a different approach by analyzing behavior variables related to the operational dimension of pedestrian behavior, namely walking speed, distance, and angles between pedestrians walking in social groups during the three phases of road crossing: before, during, and after. Furthermore, the study compared the influence of group size and sex composition on those variables when walking in groups in urban areas. The research was conducted through semi-controlled experiments on two streets in Colombia and Portugal, involving small groups of young pedestrians (1, 2, and 3) following a predefined walking path.

The findings of this study contribute to a better understanding of the impact of social factors on pedestrian behavior in different ecological contexts when walking in social groups. This information can be utilized to enhance simulation techniques, optimize pedestrian facilities, and develop effective strategies for improving road user safety by realistically modeling pedestrian operational behavior.

5.2. Materials and Methods

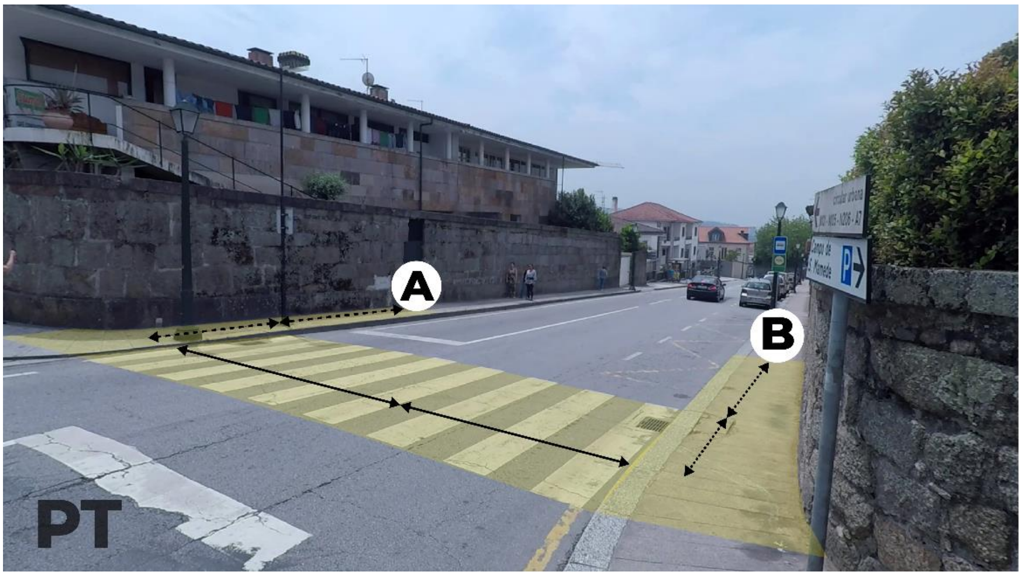
5.2.1. Experimental procedure

The experimental procedure in this chapter closely aligns with the methodology outlined in Chapter 4, Section 4.2 - Materials and Methods. However, the primary objective here was to incorporate cultural variables, leading to selecting a study site in another country with similarities to those examined in

Portugal. Consequently, the experiments were conducted on two urban streets, one in Bucaramanga, Colombia (the CO site) and the other in Guimarães, Portugal (the PT site). These locations were chosen based on their comparable attributes, as depicted in Figure 63.

(a)

(b)



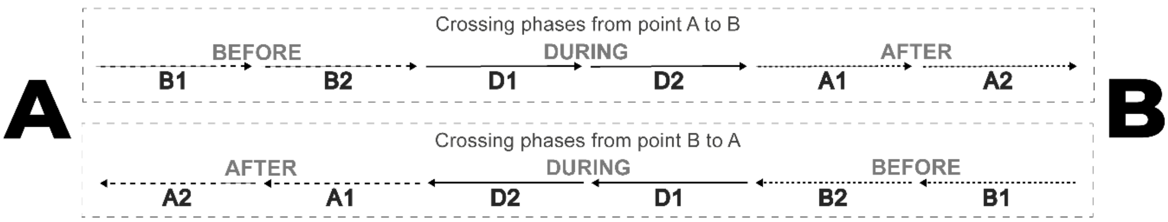


Figure 63. Study site: (a) Site CO – Carrera 27 Calle 11, Bucaramanga, Colombia; (b) Site PT - Doutor Joaquim de Meira Street, Guimarães, Portugal.

The PT site corresponds explicitly to the data collected from site S3, as previously detailed in Chapter 4. The selected streets exhibited a mixed land use, encompassing commercial and residential areas. They were characterized as collector roads lacking traffic lights but featuring a moderate volume of vehicles and pedestrians. In accordance with the Highway Capacity Manual (HCM) 2010, the sidewalks at both sites achieved a Level of Service (LOS) A. Table 34 provides an overview of the principal characteristics of each study site.

Table 34 – Main characteristics of the study sites.

Characteristics	**Study Site**	
	CO	**PT**
Road pavement	Asphalt concrete	Asphalt concrete
Park on street	yes	no
Width of the crosswalk (m)	4.120	3.994
Length of the crosswalk (m)	6.155	8.790
Average width of the lanes (m)	2.950	2.570
Effective width of the sidewalk A (m)	4.255	1.535
Effective width of the sidewalk B (m)	2.422	1.457
Pedestrian volume (15-min)	28	39
Pedestrian unit flow rate (p/min/m)	0.802	0.738

The climate of the two countries differs, with Portugal having marked seasons, while Colombia has almost insignificant temperature variations throughout the year, mainly dependent on altitude. The experiments in Guimarães were conducted from June 26 to July 5, 2019. Average temperatures ranged between 12.6°C minimum and 26.1°C maximum, according to data published by the *Instituto Português do Mar e da Atmosfera* (IPMA) (IPMA, 2019). In Bucaramanga, the experiments were conducted from December 2 to 14, 2019, during which the average temperatures, according to the Instituto de *Hidrología, Meteorología y Estudios Ambientales* (IDEAM) (IDEAM, 2019), ranged between 24-26°C (with a maximum of 28-30°C and a minimum of 18-20°C). All experiments were conducted during working hours, from 9 am to 6 pm.

A predefined circuit was established for the participants to walk in both study sites, starting from point A and proceeding to point B, then returning from point B to point A. The circuit was divided into three crossing phases: before, during, and after the road crossing. These phases were further divided into six segments: B1 and B2 (before), D1 and D2 (during), and A1 and A2 (after) (as shown in Figure 63).

The participants, formed in the six experimental groups, followed a predetermined circuit during the experiments and repeated it twice. Each experiment lasted around 40 minutes. Six experiments were conducted at each study site.

The study recruited 60 adult volunteers, 30 from the University Industrial of Santander in Colombia and 30 from the University of Minho community in Portugal. The participants consisted of 30 females and 30 males, with ages ranging from 18 to 44 years old, a mean age of 25.467 years old, and a standard deviation of 5.460 years old. Before participating in the experiments, all participants signed an informed consent form and provided demographic information, including sex and age. The detailed information about the participants can be found in Appendix A.

The experiments were recorded using a GoPro Hero5 black video camera with a 1920 × 1080 pixels resolution, a frame rate of 60 fps, and a linear range. T-Calibration, a standalone software that implements the TSAI-calibration algorithm (Tsai, 1987), was used to calibrate the video recordings, which were then analyzed using T-Analyst, a semi-automated video analysis software developed at Lund University (Johnsson et al., 2018b). T-Analyst provided the trajectories of the participants, including their x and y coordinates and walking speeds (To see more details, please refer to Section 4.2.2 – video recordings).

5.2.2. Data analysis

The database was organized including the dependent and independent variables. The dependent variables are the average walking speed, the distance, and the angles between pairs of pedestrians, calculated in the crossing phases' segments.

The data were modeled using linear mixed models (LMMs) to analyze the influence of the independent variables on the dependent ones. The hierarchical data structures had three levels. The observations corresponded to trajectories of pedestrian pairs (Pair_ID) for the distance between pedestrians and the walking speed of each pedestrian (Ped_ID). These formed part of an upper-level cluster of participant groups (Cluster_ID) (To see more details, please refer to Section 4.2.3 –Modeling pedestrian walking behavior).

The independent variables are the factors identified in the literature that influence the pedestrians' behavior, divided according to pedestrian and external factors (see Table 35).

Table 35 – Description of independent variables used in the study.

	Description variable	**Abbreviation**
Social factors	Group size: 1, 2, or 3 pedestrians	Size
	Sex composition of the group of participants: female, male and mix	Sex
	Difference between the length of the legs of each pair of pedestrians	D_Leg
	Interaction with other pedestrians: yes or no	Ped
Cultural factors	Study site	Site
External factors	Phase: before (B1 e B2), during (D1 e D2) and after (A1 e A2) the road crossing	Phase
	Effective width of zone (sidewalks or crosswalk) of each study site (m)	Width
	Approaching vehicles: yes or no	Veh

The final model presents the independent variables or interactions between these variables that were statistically significant to 5 % on the dependent variables. Data analysis was conducted using the R statistical software (R Core Team, 2021).

5.3. Results

The behavior of road users may vary across different ecological contexts due to cultural norms and a lack of awareness of traffic rules, as noted by Uzondu et al. (2020) , who emphasize the significance of formal and informal rules in shaping a country's road safety culture. In Colombia, despite the formal traffic rule that requires vehicles to yield to pedestrians in demarcated spaces for crossings, pedestrians often slow down or stop before crossing, indicating the presence of an informal rule (see Figure 64– crossing phase: B2).

This study aims to analyze the impact of social factors on the speed and spatial organization of pedestrians crossing the street in social groups across different ecological contexts. It does not examine decision-making processes related to compliance with traffic rules or waiting times. To compare these operational factors in the two study sites, the analysis of pedestrian trajectories in the Colombian site was limited, specifically to those with no longer than the maximum waiting time observed in the Portuguese site, which was 0.667 seconds (see Figure 65). This approach allows comparing pedestrian behavior under similar operational conditions across the two study sites.

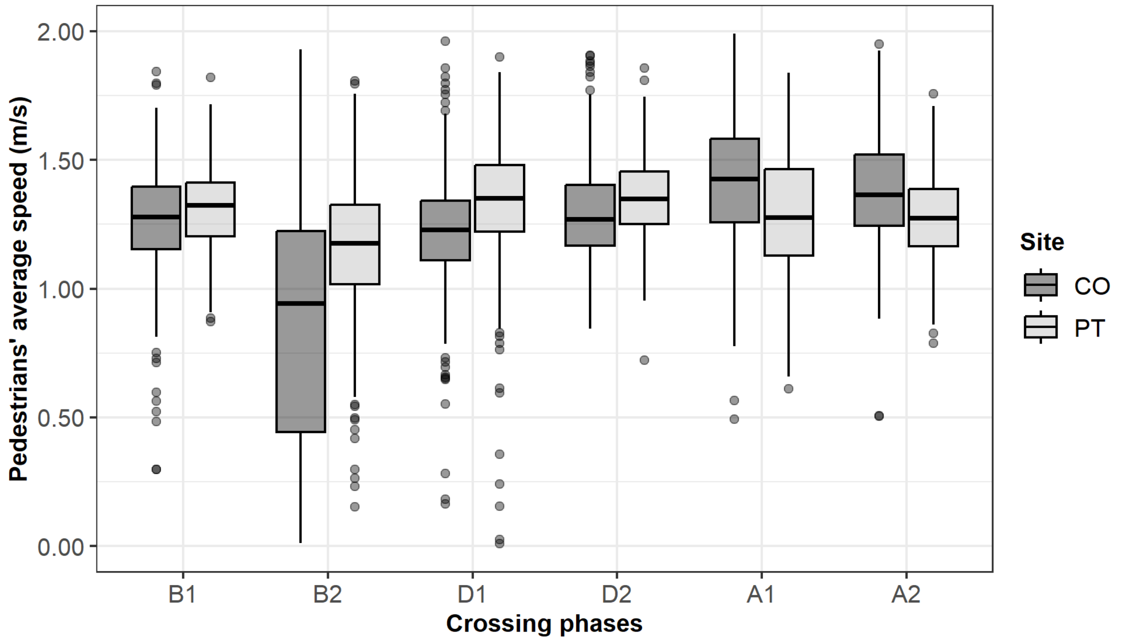


Figure 64. Average walking speed boxplot complete observed sample.

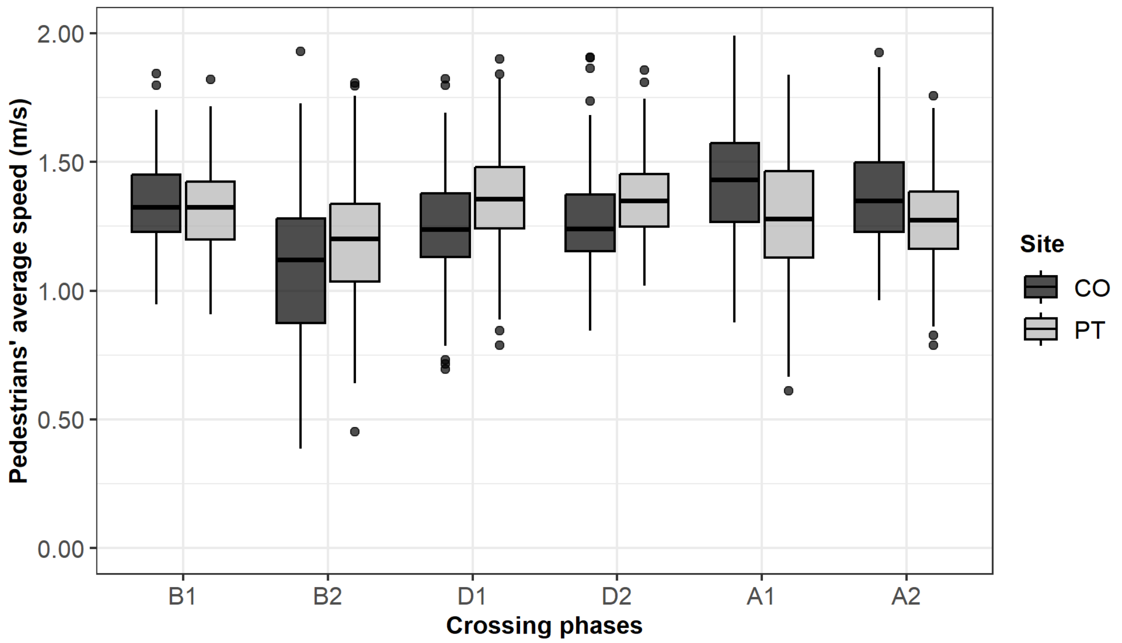


Figure 65. Average walking speed boxplot sample for analysis.

5.3.1. Average walking speed

Tables 36 and 37 present summary statistics for pedestrian walking speed in the study sites CO and PT, respectively.

Table 36 – Descriptive statistics of the pedestrians' walking speed CO.

Group of factors	Variable (Abbreviation)	Levels		CO Walking speed (m/s) Mean	Min	Max	Sd
Social factors	Size group (Size)	1		1.471	0.839	2.009	0.208
		2		1.323	0.507	1.872	0.195
		3		1.249	0.387	2.133	0.251
	Sex composition of the group of participants (Sex)	Female		1.281	0.504	2.009	0.240
		Male		1.299	0.412	1.905	0.220
		Mix		1.291	0.387	2.133	0.253
External factors	Crossing phase (Phase)	Before	B1	1.340	0.948	2.009	0.167
			B2	1.088	0.387	1.929	0.296
		During	D1	1.249	0.696	1.821	0.199
			D2	1.269	0.845	1.905	0.180
		After	A1	1.425	0.877	2.133	0.237
			A2	1.372	0.962	1.925	0.191
	Approaching vehicles (Veh)	No		1.309	0.445	2.009	0.227
		Yes		1.242	0.387	2.133	0.270
	Interaction with other pedestrians (Ped)	No		1.285	0.009	1.900	0.219
		Yes		1.254	0.580	1.857	0.240

The data reveal that, on average, both study sites demonstrate higher speeds for isolated individuals and groups of men when there are no approaching vehicles and no interactions with other pedestrians. However, there are notable differences between the two sites regarding the crossing phase. In the CO site, the highest average speed was observed after crossing the road, whereas in the PT site, it occurred during the road crossing.

Table 37 – Descriptive statistics of the pedestrians’ walking speed PT.

Group of factors	**Variable (Abbreviation)**	**Levels**		**PT Walking speed (m/s)**			
				Mean	**Min**	**Max**	**Sd**
Social factors	Size group (Size)	1		1.451	1.092	1.821	0.135
		2		1.326	0.705	1.857	0.185
		3		1.262	0.452	1.900	0.201
	Sex composition of the group of participants (Sex)	Female		1.324	0.705	1.827	0.191
		Male		1.334	0.780	1.900	0.205
		Mix		1.269	0.452	1.841	0.197
External factors	Crossing phase (Phase)	Before	B1	1.311	0.908	1.821	0.159
			B2	1.195	0.452	1.806	0.235
		During	D1	1.346	0.789	1.900	0.195
			D2	1.351	1.019	1.857	0.153
		After	A1	1.286	0.612	1.837	0.228
			A2	1.271	0.788	1.756	0.170
	Approaching vehicles (Veh)	No		1.312	0.612	1.900	0.192
		Yes		1.261	0.452	1.837	0.207
	Interaction with other pedestrians (Ped)	No		1.292	0.299	1.900	0.203
		Yes		1.268	0.698	1.857	0.224

A total of 3228 observations of pedestrians' average speed were analyzed using Linear Mixed Models (LMMs). The final model (Equation 6) includes all significant predictor variables. Satterthwaite's test results, as shown in Table 38, indicated significant effects of the interaction variables on walking speed. However, factors such as *D_Leg* (difference between leg length pair) at the social level, and *Width* (effective width of each zone) at the external level were found to be non-significant.

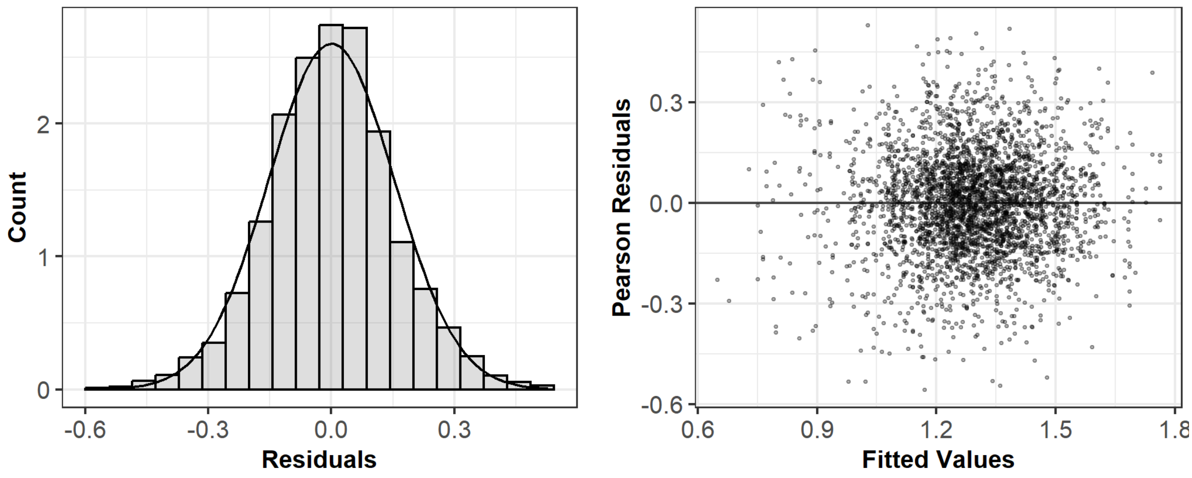
Table 38 – Satterthwaite's test results for the model for the pedestrian's average speed.

Variables	Sum Sq	NumDF	F value	p-value
Size	3.840	2.000	80.302	<0.001
Site	0.002	1.000	0.071	0.795
Sex	0.664	2.000	13.887	0.000
Veh	0.550	1.000	23.020	0.000
Phase	17.721	5.000	148.220	<0.001
Ped	0.069	1.000	2.877	0.090
Size x Site	0.216	2.000	4.516	0.011
Site x Sex	0.380	2.000	7.947	0.000
Veh x Phase	2.835	5.000	23.715	<0.001
Site x Veh	0.164	1.000	6.857	0.009
Site x Phase	7.432	5.000	62.164	<0.001
Size x Ped	0.311	2.000	6.506	0.002
Site x Veh x Phase	0.733	5.000	6.132	0.000

For $i = 1, \ldots, 12; j = 1, \ldots, 5, k = 1, \ldots, mij$, the final model for the pedestrians' average speed can be written as follows:

$$Speed_{ijk} = \beta_O + Size_{ijk} \times Site_{ijk} + Sex_{ijk} \times Site_{ijk} \\ + Phase_{ijk} \times Veh_{ijk} \times Site_{ijk} + Ped_{ijk} \times Size_{ijk} + u_{ij} + b_i + \varepsilon_{ijk} \qquad (6)$$

The diagnostic plot for the model described in Equation (6) indicates a satisfactory fit. The histogram of the residuals (Figure 63 (a)) suggests a normal distribution, indicating that the assumption of normality is met. Additionally, the plot of the residuals (Figure 63 (b)) does not reveal any systematic increase or decrease in variance, indicating that the assumption of homogeneity of residuals is also satisfied. Overall, the residuals appear to be homogeneously distributed.



(a) (b)

Figure 66. Diagnostic plots - residuals for the model (average speed): (a) Histogram of the residuals; (b) Pearson residual versus fitted values.

Table 39 and 40 provides a comprehensive presentation of the summary statistics for the model, including the full range of variables. Contrasts were used to analyze the interactions between these variables and to effectively summarize the model results for each individual variable.

Table 39 – Linear mixed model results of average walking speed (variables without interactions).

Variable	Value of category	'Speed' model (n = 3228)		
		Estimate	**SE**	**p-value**
Group sex	Female		Reference	
	Male	0.084	0.021	<0.001*
	Mix	0.068	0.016	<0.001*
Crossing phase	Phase_B1		Reference	
	Phase_B2	-0.186	0.017	<0.001*
	Phase_D1	-0.091	0.017	<0.001*
	Phase_D2	-0.085	0.017	<0.001*
	Phase_A1	0.079	0.017	<0.001*
	Phase_A2	0.011	0.017	0.517
Out-group pedestrians	Ped_No		Reference	
	Ped_Yes	0.013	0.035	0.717
Approaching vehicles	Veh_No		Reference	
	Veh_Yes	-0.037	0.023	0.114
Study site	Site_CO		Reference	
	Site_PT	-0.046	0.063	0.475

Table 40 – Linear mixed model results of average walking speed (variables with interactions).

Variable	Value of category	'Speed' model (n = 3228) Estimate	SE	p-value
Group size × Out-group pedestrians	Size_1:Ped_No	Reference		
	Size_2:Ped_Yes	-0.016	0.042	0.699
	Size_3:Ped_Yes	-0.097	0.038	0.01
Group size × Ped interaction	Size_1:Ped_No	Reference		
	Size_2:Ped_Yes	-0.016	0.042	0.699
	Size_3:Ped_Yes	-0.097	0.038	0.01
Group sex × Study site	Sex_Female:Site_PT	Reference		
	Sex_Male:Site_PT	-0.02	0.028	0.473
	Sex_Mix:Site_PT	-0.071	0.021	0.001
Crossing phase × Approaching vehicles	Phase_B1:Veh_No	Reference		
	Phase_B2:Veh_Yes	-0.223	0.032	<0.001
	Phase_D1:Veh_Yes	0.008	0.032	0.794
	Phase_D2:Veh_Yes	0.054	0.032	0.097
	Phase_A2:Veh_Yes	0.018	0.032	0.569
Crossing phase × Study site	Phase_B1:Site_CO	Reference		
	Phase_B2:Site_PT	0.096	0.023	<0.001
	Phase_D1:Site_PT	0.134	0.023	<0.001
	Phase_D2:Site_PT	0.116	0.023	<0.001
	Phase_A2:Site_PT	-0.11	0.023	<0.001
Approaching vehicles × Study site	Veh_No:Site_CO	Reference		
	Veh_Yes:Site_PT	0.025	0.03	0.399
Approaching vehicles × Study site × Crossing phase	Site_CO:Veh_No:Phase_B1	Reference		
	Site_PT:Veh_Yes:Phase_B2	0.152	0.041	<0.001
	Site_PT:Veh_Yes:Phase_D1	-0.026	0.041	0.534
	Site_PT:Veh_Yes:Phase_D2	-0.015	0.041	0.715
	Site_PT:Veh_Yes:Phase_A1	-0.001	0.041	0.979
	Site_PT:Veh_Yes:Phase_A2	-0.054	0.041	0.191
	ICC1	0.199		
	ICC2	0.388		
	AIC	-2631.3		

Significant interactions between variables were analyzed using contrasts, with the analysis of results divided into two parts: social and external factors.

5.3.1.1. Social factors

The statistical analysis of social factors demonstrated significant interactions between group size and study sites, as well as between sex compositions and the study site. The contrast results presented in Table 41 demonstrated significant differences between all group sizes within each study site. These findings are also depicted in Figure 67, which shows that the pedestrians' average speed decreases as group size increases. The highest speed was observed in singles, while the lowest was observed in triads.

Table 41 – Group size contrasts according to the study site.

Groups	CO			PT		
factors	Estimate	SE	p-value	Estimate	SE	p-value
1-2	0.164	0.025	<0.001	0.107	0.025	<0.001
1-3	0.273	0.024	<0.001	0.199	0.024	<0.001
2-3	0.110	0.017	<0.001	0.092	0.015	<0.001

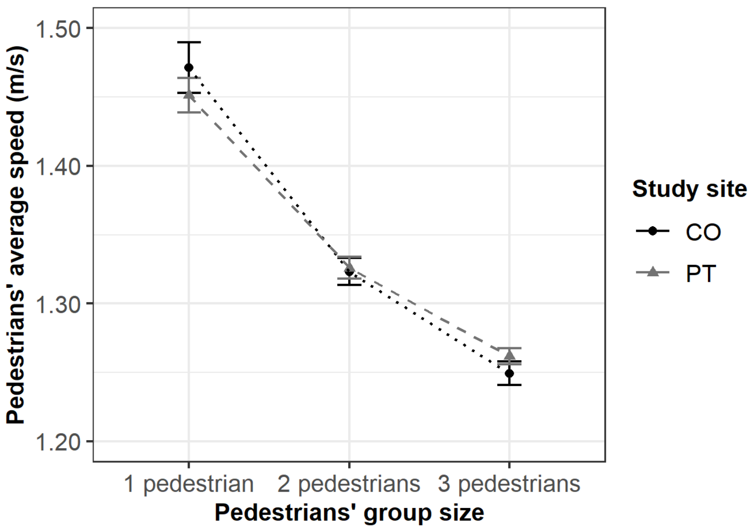


Figure 67. Pedestrians' average speed and respective standard error according to the study site per group size.

When comparing each group size between the CO and PT sites, both graphically (Figure 67) and based on the model results presented in Table 42, it can be concluded that there were no significant differences in group size between the CO and PT sites (p-value > 0.05).

Table 42 – Study site contrasts according to the group size.

Group factors	CO site compared to PT site		
	Estimate	SE	p-value
1	0.029	0.065	0.667
2	-0.028	0.062	0.659
3	-0.046	0.062	0.472

When considering the sex composition of the groups, it appears that the average speed in both study sites is higher for all-male groups (Figure 68). However, no significant differences were observed among the different sexes (Table 43).

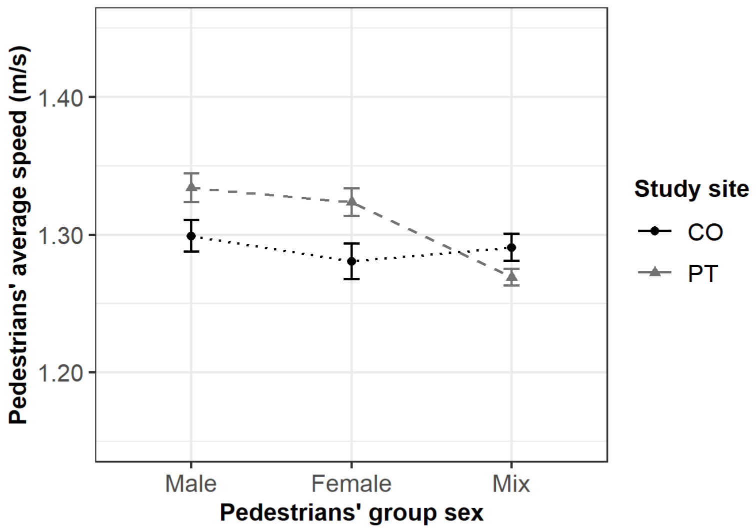


Figure 68. Pedestrians' average speed and respective standard error according to the study site per group sex.

Table 43 – Group sex contrasts according to the study site.

Groups factors	CO			PT		
	Estimate	SE	p-value	Estimate	SE	p-value
Female - Male	-0.084	0.021	<0.001	-0.064	0.019	0.002
Female - Mix	-0.068	0.016	<0.001	0.003	0.014	0.976
Male - Mix	0.016	0.016	0.546	0.067	0.014	<0.001

At the CO site, the female group exhibited a significant difference from the male and mixed groups (p-value < 0.05). The negative coefficient associated with this contrast indicated that female pedestrians walked at a lower speed. At the PT site, the male groups showed significant differences from the female and mixed groups (p-value < 0.05). The negative and the positive coefficient, respectively, associated with this contrast indicated that male pedestrians walked at a higher average speed.

Based on the contrast results for comparing the two study sites (Table 44), it can be concluded that there were no significant differences in terms of group sex composition between the CO and PT sites (p-value > 0.05).

Table 44 – Study site contrasts according to the group sex.

Group factors	CO site compared to PT site		
	Estimate	**SE**	**p-value**
Female	-0.032	0.065	0.625
Male	-0.012	0.065	0.855
Mix	0.039	0.064	0.550

5.3.1.2. External factors

In the context of external factors, the analysis of the model indicated two significant interactions between the variables: (i) Phase, Vehicle, and Site, and (ii) Ped with Size. These findings highlight the interplay between pedestrian behavior, the specific crossing phase, presence of vehicles, interactions with out-group pedestrians and the study site.

The average speed of pedestrians varied depending on the crossing phases in both study sites, regardless of the presence or absence of approaching vehicles (refer to Figure 69). Specifically, in both study sites, the average speed of pedestrians decreased as they approached the road crossing (segment B2) and increased at the crosswalk.

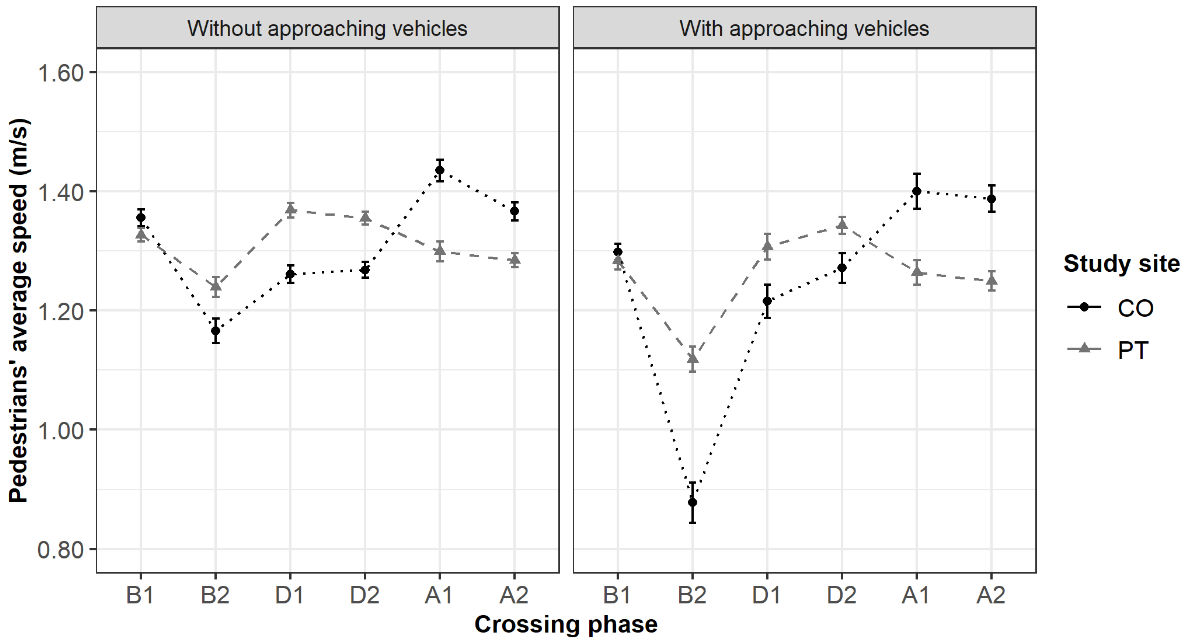


Figure 69. Pedestrians' average speed and respective standard error according to the study site and the presence of approaching vehicles, per crossing phase.

According to the contrast results presented in Table 45, significant differences (p-value < 0.05) were observed in the average pedestrian speed within the two segments before the road crossing (B2-B1) and during the transitions of the crossing phases (B2-D1: before to during, and D2-A1: during to after) in both study sites, regardless of the presence of approaching vehicles.

The positive coefficient associated with the B1-B2 contrast indicates that the average speed of pedestrians decreases before the road crossing. Conversely, the negative coefficients at B2-D1 suggest an increased pedestrian speed during the road crossing.

However, there is a difference in the coefficient at D2-A1 depending on the study site. In the CO site, the negative coefficient indicates that the pedestrian average speed increases after the road crossing. On the other hand, in the PT site, the average speed decreases after the road crossing, regardless of the presence of approaching vehicles. No significant differences (p-value > 0.05) in average speed were observed between the two segments during the road crossing in both study sites, irrespective of the presence of approaching vehicles.

Table 45 – Crossing phase contrasts by the presence of approaching vehicles according to the study site.

Approaching vehicles	Crossing phase	CO			PT		
		Estimate	SE	p-value	Estimate	SE	p-value
Without	B1 - B2	0.186	0.017	<0.001	0.090	0.016	<0.001
	B2 - D1	-0.095	0.017	<0.001	-0.133	0.016	<0.001
	D1 - D2	-0.006	0.017	0.999	0.011	0.016	0.983
	D2 - A1	-0.164	0.017	<0.001	0.062	0.016	0.001
	A1 - A2	0.068	0.017	<0.001	0.011	0.016	0.982
With	B1 - B2	0.409	0.028	<0.001	0.161	0.021	<0.001
	B2 - D1	-0.326	0.028	<0.001	-0.186	0.021	<0.001
	D1 - D2	-0.052	0.028	0.423	-0.045	0.021	0.251
	D2 - A1	-0.129	0.028	<0.001	0.083	0.021	<0.001
	A1 - A2	0.016	0.028	0.992	0.012	0.021	0.992

According to the contrast results presented in Table 46, when comparing each segment of the crossing phases between the two study sites, significant differences in average speeds were observed only in segment B2 when there were approaching vehicles. This finding suggests that in Colombia, pedestrians yield to vehicles, leading to a more significant decrease in average speed before crossing compared to the PT site.

Table 46 – Study site contrasts by crossing phases according to the presence of approaching vehicles.

Crossing phase	CO site compared to PT site					
	Without approaching vehicles			With approaching vehicles		
	Estimate	SE	p-value	Estimate	SE	p-value
B1	0.033	0.064	0.613	0.008	0.066	0.910
B2	-0.063	0.064	0.335	-0.240	0.066	0.002
D1	-0.101	0.064	0.131	-0.100	0.066	0.146
D2	-0.083	0.064	0.207	-0.093	0.066	0.174
A1	0.143	0.064	0.039	0.119	0.066	0.089
A2	0.085	0.064	0.197	0.114	0.066	0.100

Additionally, when there were no approaching vehicles, a significant difference in average speed was observed after the road crossing in segment A1. This indicates that the average speed in the CO site was higher than in the PT site in segment A1 (after the road crossing).

Furthermore, the model results revealed that interactions with out-group pedestrians, based on group size, had an impact on the speed of pedestrians. The contrast analysis, which compared the presence or absence of interactions with other pedestrians for each group size, indicated a significant difference in average speed for groups of three pedestrians ($\hat{\beta}$=0.080, SE=0.015, p-value<0.001). However, no significant effect was observed for singles ($\hat{\beta}$=-0.010, SE=0.035, p-value=0.769) and dyads ($\hat{\beta}$=-0.001, SE=0.024, p-value=0.954) (see Figure 70).

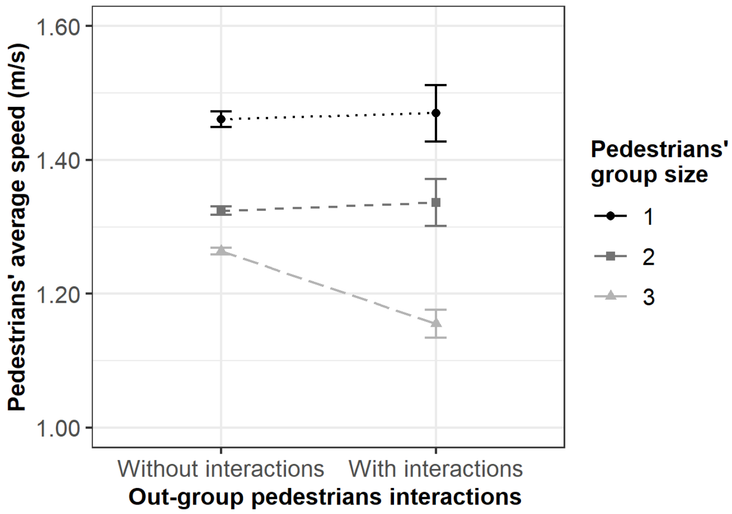


Figure 70. Pedestrians' average speed and respective standard error according to the study site per group size.

According to the contrast results presented in Table 47, significant differences in average speed were observed between group sizes (p-value < 0.05), irrespective of whether there were interactions with out-group pedestrians. This finding aligns with the previous information regarding the effect of group size on average speed.

Table 47 – Group size contrasts according to the interaction with out-group pedestrians.

Pedestrians' group size	Without interaction			With interaction		
	Estimate	SE	p-value	Estimate	SE	p-value
1-2	0.127	0.013	<0.001	0.136	0.041	0.003
1-3	0.188	0.013	<0.001	0.278	0.037	<0.001
2-3	0.060	0.007	<0.001	0.142	0.027	<0.001

5.3.2. Average distance between pairs of pedestrians

Table 48 and Table 49 present the summary statistics for the average distance between pedestrians based on analysis factors and study sites.

Table 48 – Descriptive statistics of the distance between pairs of pedestrians CO.

Group of factors	Variable (Abbreviation)	Levels		Site CO – Distance (cm)			
				Mean	Min	Max	Sd
Social factors	Size group (Size)	2		76.226	40.608	116.632	14.669
		3		75.658	31.602	155.668	18.287
	Group sex composition (Sex)	Female		71.685	31.602	126.881	17.152
		Male		76.93	39.133	138.31	16.743
		Mix		77.896	36.606	155.668	17.448
External factors	Crossing phase (Phase)	Before	B1	75.122	42.585	120.342	13.684
			B2	68.694	31.602	148.175	17.887
		During	D1	72.376	41.157	129.676	16.247
			D2	74.262	38.882	155.668	17.762
		After	A1	83.596	38.56	145.136	17.638
			A2	80.886	49.896	137.684	16.557
	Approaching vehicles (Veh)	No		76.417	37.169	148.175	17.482
		Yes		75.159	31.602	155.668	17.316
	Interaction with other pedestrians (Ped)	No		75.997	31.602	155.668	17.284
		Yes		72.994	36.606	148.175	19.025

The results indicate that, on average, pedestrians tend to maintain a greater distance in triads and when interacting with other pedestrians in both study sites. However, some differences were observed between the two study sites regarding certain factors.

Specifically, at the CO site, the highest average distance was observed for mixed groups after crossing the road and in the absence of approaching vehicles (Table 48). In contrast, at the PT site, the highest average distance was detected for all-male groups, during road crossing, and in the presence of approaching vehicles (Table 49).

Table 49 – Descriptive statistics of the distance between pairs of pedestrians PT.

Group of factors	Variable (Abbreviation)	Levels		Site PT – Distance (cm) Mean	Min	Max	Sd
Social factors	Size group (Size)	2		83.974	45.288	155.506	18.706
		3		89.084	38.481	232.24	27.345
	Group sex composition (Sex)	Female		85.698	47.745	232.24	24.027
		Male		94.154	46.523	225.382	29.814
		Mix		85.247	38.481	155.506	22.853
External factors	Crossing phase (Phase)	Before	B1	81.003	47.101	134.541	20.524
			B2	92.997	48.013	204.681	25.012
		During	D1	93.912	51.237	225.061	24.302
			D2	89.11	47.468	154.421	19.591
		After	A1	87.716	45.288	232.24	32.797
			A2	81.603	38.481	174.773	25.43
	Approaching vehicles (Veh)	No		86.29	38.481	225.382	25.575
		Yes		89.74	46.523	232.24	25.223
	Interaction with other pedestrians (Ped)	No		87.947	38.481	232.24	25.474
		Yes		84.907	48.346	154.421	25.46

A total of 2111 observations of the average distances between pairs of pedestrians were analyzed using LMMs. As explained in section 4.2.3, the models accounted for random effects using the ID of the pair of participants and the ID of the group of participants.

The final model included all significant predictor variables (Equation 7). The results of the Satterthwaite test indicated significant interactions for certain variables, as shown in Table 50. However, the following social factor was found to be non-significant *D_Leg* (difference between legs length). Additionally, the following external factors were non-significant: *Width* (effective width of each zone), and *Ped* (interactions with out-group pedestrians).

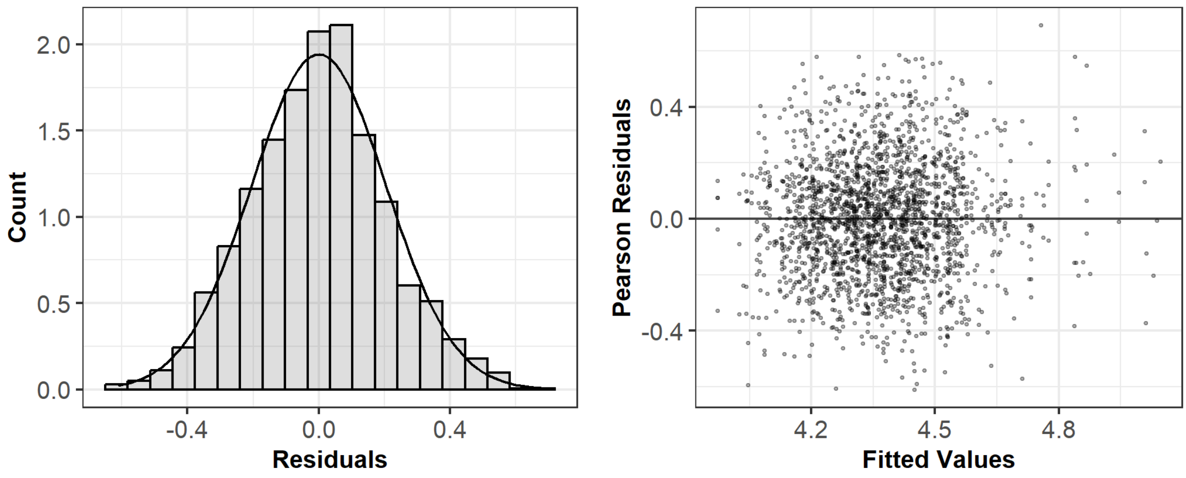
For $i = 1, \dots, 12; j = 1, \dots, 5, k = 1, \dots, mij,$ the model of the average distance, can be written as

$$\log(D)_{ijk} = \beta_O + Size_{ijk} \times Sex_{ijk} \times Site_{ijk} + Phase_{ijk} \times Veh_{ijk} \times Site_{ijk} + u_{ij} + b_i + \varepsilon_{ijk} \quad (7)$$

Table 50 – Satterthwaite's test results for the model of the average distance between pairs of pedestrians.

Variables	**Sum Sq**	**NumDF**	**F value**	**p-value**
Size	0.043	1.000	0.991	0.320
Sex	0.471	2.000	5.412	0.007
Site	0.470	1.000	10.811	0.005
Veh	0.324	1.000	7.460	0.006
Phas	1.515	5.000	6.972	0.000
Size x Sex	0.478	2.000	5.492	0.004
Size x Site	0.024	1.000	0.561	0.454
Sex x Site	0.276	2.000	3.179	0.049
Veh x Phase2	1.613	5.000	7.422	0.000
Site x Veh	0.236	1.000	5.429	0.020
Site x Phase	7.098	5.000	32.658	<0.001
Size x Sex x Site	0.336	2.000	3.870	0.021
Site x Veh x Phase	0.682	5.000	3.137	0.008

Based on the diagnostic plot for the model described in Equation (7), the histogram of the residuals indicates a normal distribution (Figure 71 (a)). Additionally, there is no apparent systematic increase or decrease in the variance of the residuals (Figure 71 (b)). Furthermore, the residuals appear to be homogeneously distributed, indicating that the model assumptions are reasonably met.



(a) (b)

Figure 71. Diagnostic plots - residuals for the model (average distance): (a) Histogram of the residuals; (b) Pearson residual versus fitted values.

The full summary statistics of the model are presented in Table 51 and Table 52.

Table 51 – Linear mixed model result of distance between pedestrians (variables without interactions).

Variable	Value of category	'Distance' model (n =2111)		
		Estimate	SE	p-value
Group size	Size_2	Reference		
	Size_3	0.144	0.035	<0.001
Group sex	Sex_Female	Reference		
	Sex_Male	0.252	0.073	0.001
	Sex_Mix	0.251	0.061	<0.001
Crossing phase	Phase_B1	Reference		
	Phase_B2	-0.089	0.031	0.004
	Phase_D1	-0.06	0.031	0.053
	Phase_D2	-0.041	0.031	0.179
	Phase_A1	0.074	0.031	0.017
	Phase_A2	0.049	0.031	0.11
Approaching vehicles	Veh_No	Reference		
	Veh_Yes	-0.015	0.032	0.634
Study site	Site_CO	Reference		
	Site_PT	0.242	0.084	0.005

Table 52 – Linear mixed model result of distance between pedestrians (variables with interactions).

Variable	**Value of category**	**'Distance' model (n =2111)**		
		Estimate	**SE**	**p-value**
Group sex × Group Size	Sex_Female:Size_2		Reference	
	Sex_Male:Size_3	-0.163	0.049	0.001
	Sex_Mix:Size_3	-0.196	0.045	<0.001
Group Size × Study site	Size_2:Site_CO		Reference	
	Size_3:Site_PT	-0.135	0.055	0.014
Group sex × Group Size	Sex_Female:Site_CO		Reference	
	Sex_Male:Site_PT	-0.14	0.104	0.178
	Sex_Mix:Site_PT	-0.261	0.088	0.004
Crossing phase × Approaching vehicles	Phase_B1:Veh_No		Reference	
	Phase_B2:Veh_Yes	-0.037	0.044	0.401
	Phase_D1:Veh_Yes	0.028	0.044	0.526
	Phase_D2:Veh_Yes	0.036	0.044	0.418
	Phase_A2:Veh_Yes	0.052	0.044	0.238
Approaching vehicles × Study site	Veh_No:Site_CO		Reference	
	Veh_Yes:Site_PT	-0.039	0.046	0.4
Crossing phase × Study site	Phase_B1:Site_CO		Reference	
	Phase_B2:Site_PT	0.195	0.043	<0.001
	Phase_D1:Site_PT	0.196	0.043	<0.001
	Phase_D2:Site_PT	0.084	0.043	0.048
	Phase_A2:Site_PT	-0.137	0.043	0.001
Group size × Group sex × Study site	Size_2:Sex_Female:Site_PT		Reference	
	Size_3:Sex_Male:Site_PT	0.168	0.073	0.022
	Size_3:Sex_Mix:Site_PT	0.174	0.066	0.008
Approaching vehicles × Study site × Crossing phase	Site_CO:Veh_No:Phase_B1		Reference	
	Site_PT:Veh_Yes:Phase_B2	0.095	0.063	0.135
	Site_PT:Veh_Yes:Phase_D1	0	0.064	0.995
	Site_PT:Veh_Yes:Phase_D2	0.102	0.064	0.11
	Site_PT:Veh_Yes:Phase_A1	0.21	0.063	0.001
	Site_PT:Veh_Yes:Phase_A2	0.12	0.064	0.061
ICC1			0.281	
ICC2			0.067	
AIC			-388.6	

5.3.2.1. Social factors

Regarding social factors results showed a statistically significant interaction between group size, sex, and study site. Figure 72 hints that the distances between pedestrians were higher in the PT site compared to the CO site.

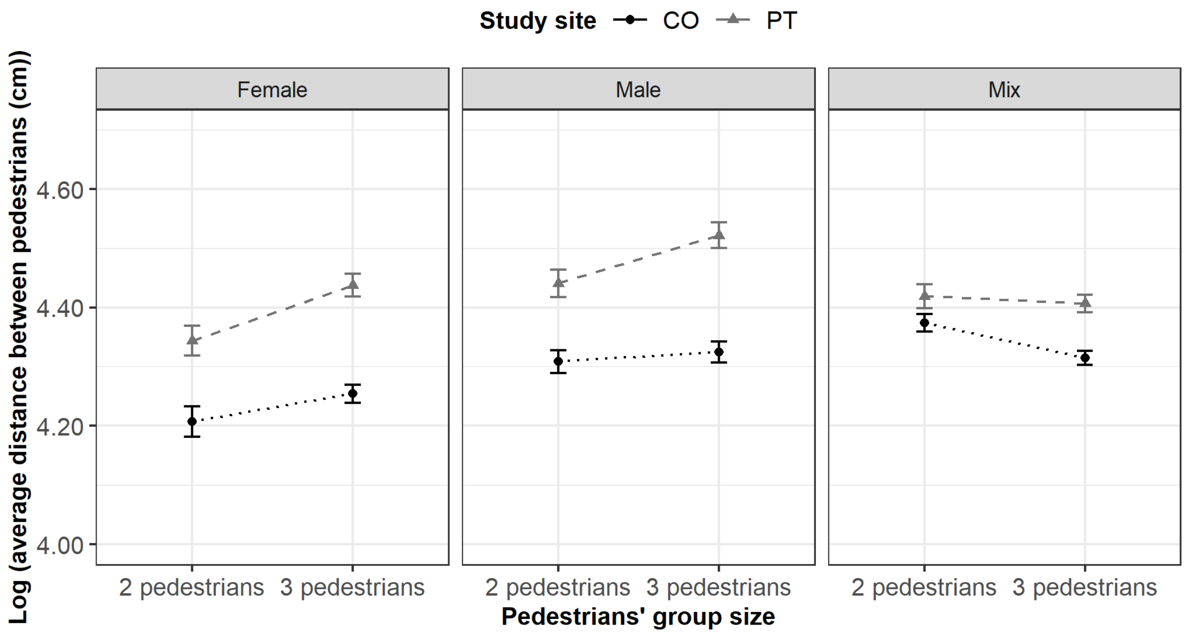


Figure 72. Average distance between pairs of pedestrians and respective standard error according to the study site per group sex and size.

However, the contrast results in Table 53, reaching the average distance between the study sites according to the group size and sex, revealed significant differences between the two study sites only in females' and males' triads and females' dyads (p-value<0.05).

Table 53 – Study site contrasts per group sex into each the group size.

Pedestrians' group sex	**CO site compared to PT site**					
	2 pedestrians			**3 pedestrians**		
	Estimate	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
Female	-0.302	0.085	0.001	-0.167	0.072	0.024
Male	-0.162	0.087	0.065	-0.195	0.077	0.014
Mix	-0.041	0.069	0.550	-0.081	0.063	0.208

In all these cases, the negative coefficients indicated that the average distance between pedestrians in the CO site is lower than in the PT site. However, the differences in mixed groups were insignificant (p-value>0.05).

The contrast results comparing the average distance between group sizes according to the group sex inside each study site revealed that there were significant differences between dyads and triads in female groups only in the CO site (p-value<0.05) (Table 54). The negative coefficient suggests that females in dyads tend to walk closer than females in triads. In the PT site, no significant differences were observed between group sizes (p-value>0.05).

Table 54 – Group size contrasts per group sex according to the study site.

Pedestrians' group sex	Dyad compare with triad					
	CO			PT		
	Estimate	SE	p-value	Estimate	SE	p-value
Female	-0.144	0.036	<0.001	-0.009	0.043	0.837
Male	0.019	0.035	0.589	-0.014	0.036	0.691
Mix	0.052	0.029	0.071	0.013	0.024	0.585

Results of the contrast analysis, which compared the average distances between sex compositions according to the group size within each study site (Table 55), revealed significant differences between female-male and female-mixed dyads in the CO site (p-value<0.05).

Table 55 – Group sex composition contrasts per group size into each study site.

Group sex	Group Size	CO Site			PT Site		
		Estimate	SE	p-value	Estimate	SE	p-value
Female - Male	Dyad	-0.252	0.077	0.004	-0.112	0.077	0.320
Female - Mix	Dyad	-0.251	0.063	0.000	0.010	0.067	0.987
Male - Mix	Dyad	0.002	0.067	1.000	0.122	0.065	0.148
Female - Male	Triad	-0.090	0.065	0.358	-0.117	0.062	0.147
Female - Mix	Triad	-0.054	0.051	0.543	0.032	0.054	0.823
Male - Mix	Triad	0.035	0.058	0.814	0.150	0.055	0.021

The negative coefficient suggests that females tend to walk closer to each other compared to males and mixed dyads. On the other hand, in the PT site, significant differences were observed between male and mixed triads (p-value<0.05), with a positive coefficient indicating that males tend to walk further apart than in mixed groups.

5.3.2.2. External factors

Regarding external factors, a statistically significant interaction was found between the presence of approaching vehicles, crossing phases, and the study site. Figure 73 illustrates that the average distance between pedestrians varied between the study sites during the crossing phases. As pedestrians approached the crosswalk at the PT site, their distance increased and decreased after crossing the road. In contrast, at the CO site, the distance between pedestrians decreased before the road crossing but increased during and after the crossing.

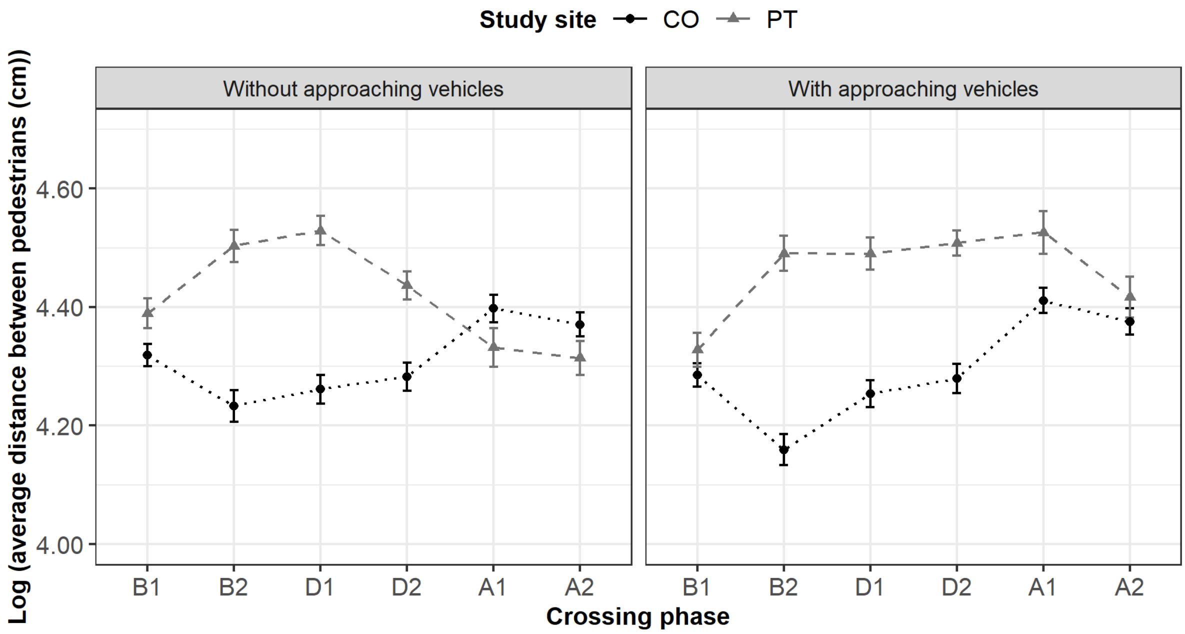


Figure 73. Average distance between pairs of pedestrians and respective standard error according to the study site per crossing phases and the presence of approaching vehicles.

As seen in Figure 74, pedestrians at the CO site tend to walk close to each other during street crossings and then increase the distance between them after crossing. This behavior could be due to their perception that they do not have the right of way over vehicles, which leads them to wait for each other and cross closer together to feel safer.

Figure 74. Frame sequence for different crossing phases of the trajectories of two groups of pedestrians in the CO site.

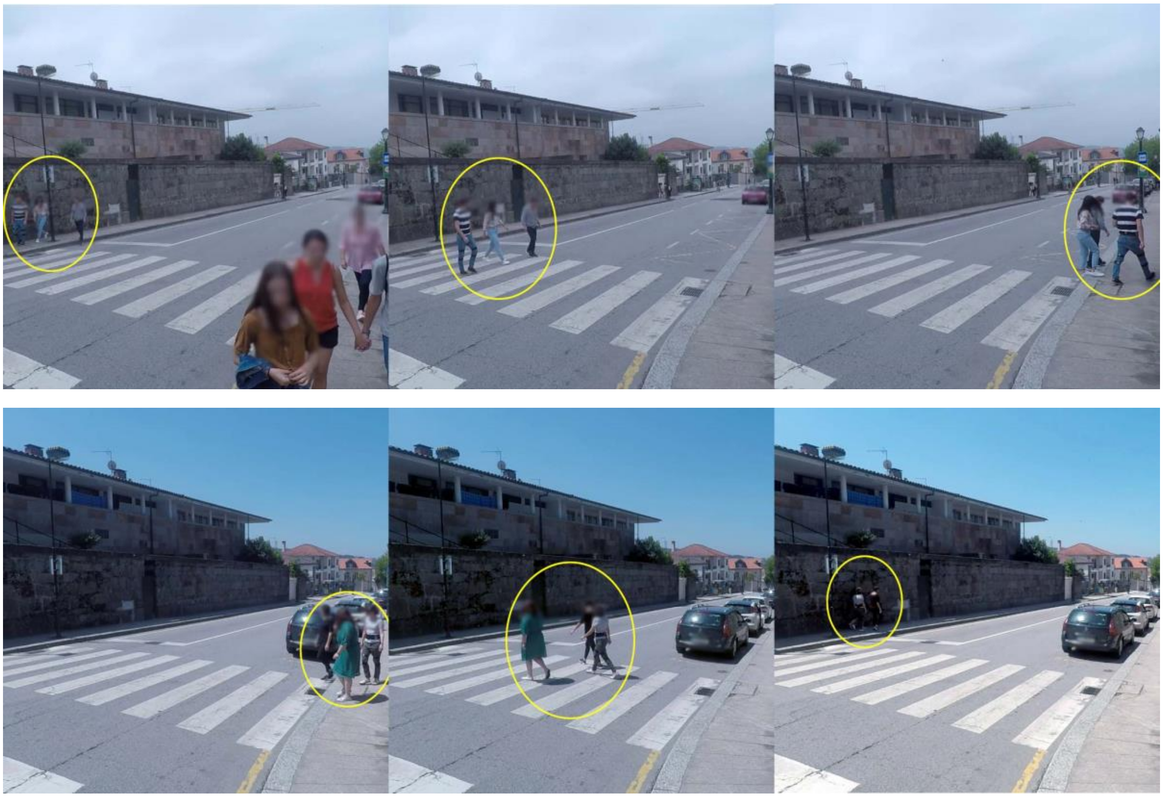


Figure 75. Frame sequence for different crossing phases of the trajectories of two groups of pedestrians in the PT site.

In contrast, at the PT site, as seen in Figure 75, pedestrians tend to increase their interpersonal distance before crossing since the first person to arrive at the crosswalk tends to cross without waiting for their companions, increasing the distance between them.

This behavior may be due to the perception of the pedestrian crossing as a safe zone. Another possible explanation is that the crosswalk is wider than the sidewalks, which may allow pedestrians to spread out more. However, zone width was not a significant independent variable in this study, possibly due to the limited variability of the two study locations. Future research could further explore this variable.

The contrast results presented in Table 56 compared the segments of the crossing phases according to each study site and with or without approaching vehicles. The results showed significant differences without approaching vehicles at segments D2-A1 in both study sites and at segments B1-B2 in the PT site (p-value<0.05).

Table 56 – Crossing phases contrast per presence of approaching vehicles according to the study site.

Approaching vehicles	**Crossing phase**	**CO**			**PT**		
		Estimate	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
Without	B1 - B2	0.089	0.032	0.065	-0.098	0.030	0.016
	B2 - D1	-0.029	0.032	0.945	-0.042	0.030	0.734
	D1 - D2	-0.018	0.032	0.993	0.077	0.030	0.116
	D2 - A1	-0.115	0.032	0.005	0.118	0.030	0.001
	A1 - A2	0.024	0.032	0.977	0.003	0.030	1.000
With	B1 - B2	0.144	0.032	0.000	-0.178	0.034	<.0001
	B2 - D1	-0.097	0.032	0.026	0.023	0.034	0.985
	D1 - D2	-0.035	0.032	0.876	-0.019	0.034	0.993
	D2 - A1	-0.129	0.032	0.001	0.004	0.034	1.000
	A1 - A2	0.048	0.032	0.663	0.094	0.034	0.057

In segments D2-A1, the coefficients differed by study site. The negative coefficient in the CO site indicated that the average distance between pedestrians increased after the road crossing. In contrast, the positive coefficient in the PT site suggested that the distance decreased after the road crossing. In the PT site, the negative coefficient at B1-B2 segments indicated that the average distance between pedestrians increased before the road crossing.

In the presence of approaching vehicles, there were significant differences between the B1-B2 segments in both study sites (p-value<0.05), with a positive coefficient indicating an increase in the average distance between pedestrians in the CO site and a negative coefficient indicating a decrease in the PT site. Additionally, there were significant differences in the CO site between the B2-D1 and D2-A1 segments (p-value<0.05), with a negative coefficient suggesting an increase in the average distance during the road crossing and a decrease after.

The contrast results comparing the two study sites according to each segment of crossing phases and the presence or absence of approaching vehicles (Table 57) showed significant differences at segments B2, D1, and D2 in both study sites without and with approaching vehicles. With approaching vehicles, there is also a significant difference at segment A1 (p-value<0.05). In all cases, the negative coefficient indicates that the average distances between pairs of pedestrians are lower in the CO site than the PT site.

Table 57 – Study site contrast per Crossing phases according to the presence of approaching vehicles.

Crossing phase	CO site compared to PT site					
	Without approaching vehicles			With approaching vehicles		
	Estimate	SE	p-value	Estimate	SE	p-value
B1	-0.106	0.065	0.113	-0.082	0.066	0.224
B2	-0.293	0.065	0.000	-0.405	0.066	<.0001
D1	-0.306	0.065	0.000	-0.285	0.066	0.000
D2	-0.211	0.065	0.003	-0.269	0.066	0.000
A1	0.022	0.065	0.733	-0.136	0.066	0.047
A2	0.001	0.065	0.983	-0.090	0.066	0.186

5.3.3. Average angle of pedestrian pairs

Table 58 and Table 59 present the summary statistics for the average angles of pedestrians, considering different analysis factors and study sites.

Table 58 – Descriptive statistics of the angles between pairs of pedestrians (CO).

Group of factors	Variable (Abbreviation)	Levels		Site CO – Angle (º) Mean	Min	Max	SD
Social factors	Size group (Size)	2 (Pair A)		91.537	17.963	161.529	21.552
		3 (Pair B)		110.018	14.478	172.684	27.180
		3 (Pair C)		73.371	8.384	161.640	27.979
	Sex composition of the group of participants (Sex)	Female		91.612	11.155	172.175	31.182
		Male		88.385	8.384	172.225	30.343
		Mix		93.586	18.604	172.684	30.237
External factors	Crossing phase (Phase)	Before	B1	84.525	14.535	154.471	25.628
			B2	92.13	14.478	172.684	35.207
		During	D1	88.359	13.174	172.175	27.966
			D2	92.72	8.384	162.318	28.136
		After	A1	102.623	30.031	172.225	33.864
			A2	90.983	22.068	153.357	28.975
	Approaching vehicles (Veh)	No		89.268	8.384	172.225	30.381
		Yes		94.273	11.155	172.684	30.643
	Interaction with other pedestrians (Ped)	No		91.682	8.384	172.225	30.455
		Yes		93.053	32.825	172.684	32.982

The highest average angle was observed for type pair B (triads), in mixed groups, after crossing the road (A1), in the presence of approaching vehicles, and interactions with out-group pedestrians in both study sites. Notably, the average angles in the PT site appear to be substantially higher across all variables (Table 59).

Table 59 – Descriptive statistics of the angles of pedestrians (PT).

Group of factors	Variable (Abbreviation)	Levels		Site PT – Angle (º) Mean	Min	Max	Sd
Social factors	Size group (Size)	2 (Pair A)		103.604	20.303	177.811	30.549
		3 (Pair B)		112.818	20.550	178.337	37.905
		3 (Pair C)		90.887	3.483	176.902	41.746
	Sex composition of the group of participants (Sex)	Female		100.037	3.483	178.337	38.504
		Male		103.279	18.862	177.106	40.145
		Mix		103.756	3.852	178.035	37.601
External factors	Crossing phase (Phase)	Before	B1	91.690	3.852	178.337	40.441
			B2	100.459	19.703	173.429	42.475
		During	D1	93.568	11.903	166.732	31.672
			D2	101.801	23.557	169.534	27.712
		After	A1	117.602	18.862	177.811	38.174
			A2	110.624	3.483	177.106	42.449
	Approaching vehicles (Veh)	No		99.697	3.483	178.337	36.404
		Yes		106.859	3.852	177.825	41.028
	Interaction with other pedestrians (Ped)	No		102.00	3.483	178.337	38.369
		Yes		110.282	22.693	176.902	39.327

A total of 2149 observations of the average angles between pairs of pedestrians were analyzed in the two study sites. As described in section 4.2.3, the models accounted for random effects using the ID of the pair of participants and the ID of the group of participants. In the analysis of angles of pedestrians, a subdivision based on group size was introduced. The pair of dyads was referred to as pair A, and for triads, the first pair was denoted as pair B, and the second pair as pair C (refer to Figure 76).

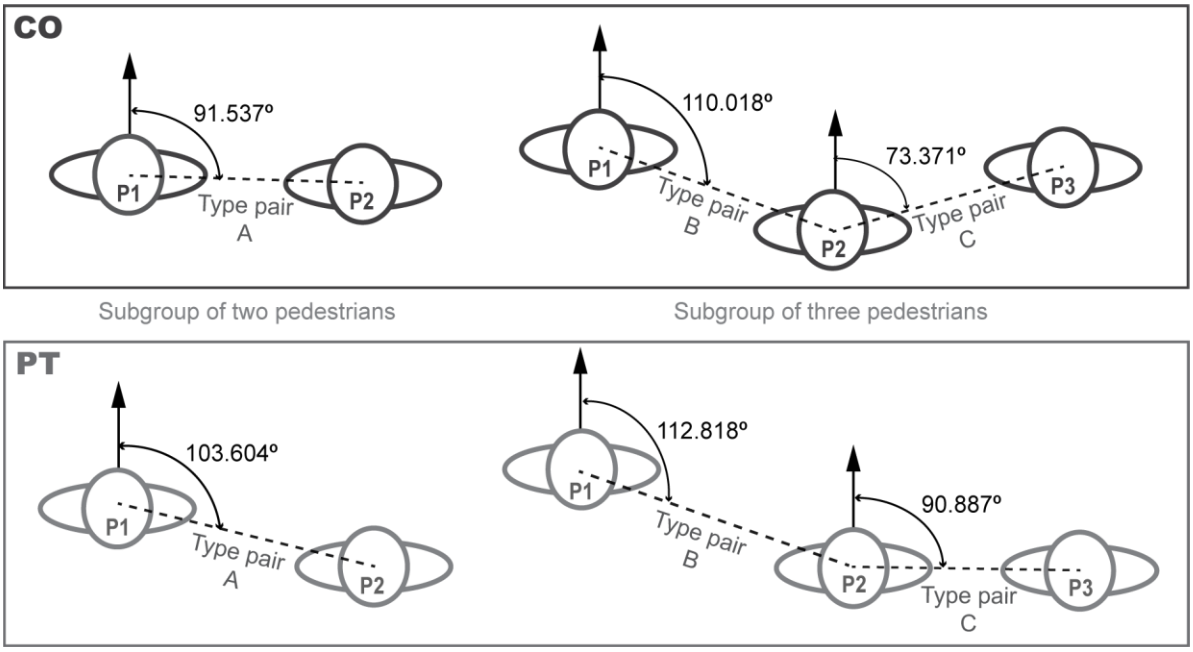


Figure 76. Type of pairs according to the group size with average angles of pedestrians by study site.

The LMMs were employed to fit the model for the average angles of pedestrians, similar to the approach used for pedestrians' walking speed. The final model includes all significant predictor variables (Equation 8).

For $i = 1, \dots, 12; j = 1, \dots, 5, k = 1, \dots, mij,$ the model of the average distance, can be written as

$$A_{ijk} = \beta_O + Type\_Pair_{ijk} \times Site_{ijk} + Phase_{ijk} + Veh_{ijk} + u_{ij} + b_i + \varepsilon_{ijk} \qquad (8)$$

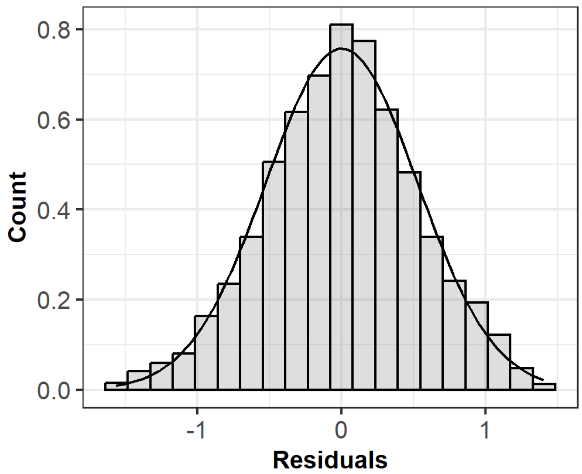
Satterthwaite's test was conducted to identify the variables and interactions that significantly influence the average angles of pedestrians, and the results are presented in Table 60.

Table 60 – Satterthwaite's test results for the model of the average angle of pedestrian pairs.

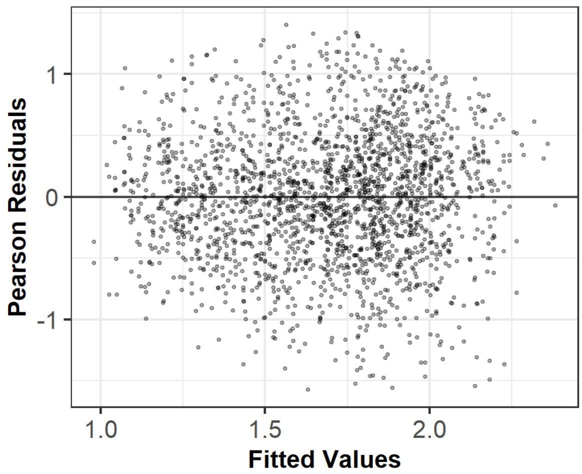
Variables	**Sum Sq**	**NumDF**	**F value**	**p-value**
Type_Pair	92.940	2.000	165.090	<0.001
Site	7.148	1.000	25.394	<0.001
Phase	29.176	5.000	20.730	<0.001
Veh	5.042	1.000	17.913	<0.001
Type_Pair x Site	7.100	2.000	12.613	<0.001

Among the social factors, *D_Leg* (legs length) was found to be non-significant. In addition, several external factors, including *Ped* (interactions with out-group pedestrians), *Pav* (pavement), *W_Lanes* (lane width), *L_Crosswalk* (crosswalk length), and *Dist* (Distance from the crosswalk to the nearest intersection).

Based on the diagnostic plot for the model described in Equation (8), the histogram of the residuals suggests that they follow a normal distribution (Figure 77 (a)). Furthermore, there is no apparent systematic increase or decrease in the variance of the residuals (Figure 77 (b)). These observations indicate that the residuals are homogeneously distributed, which supports the assumption of homoscedasticity in the model.



(a)



(b)

Figure 77. Diagnostic plots - residuals for the model (average angle): (a) Histogram of the residuals; (b) Pearson residual versus fitted values.

The summary statistics of the model can be found in Table 61. Contrasts were employed to examine the interactions between variables and provide a comprehensive overview of the model results for each variable.

Table 61 – Linear mixed model results of average angle of pedestrian pairs.

Variable	Value of category	'Angle' model (n =2149)		
		Estimate	**SE**	**p-value**
Site	Site_CO		Reference	
	Site_PT	0.234	0.059	0.000
Type of pair	Type_A		Reference	
	Type_B	0.285	0.044	0.000
	Type_C	-0.340	0.044	0.000
Crossing phase	Phase_B1		Reference	
	Phase_B2	0.142	0.040	0.000
	Phase_D1	0.045	0.040	0.255
	Phase_D2	0.158	0.040	0.000
	Phase_A1	0.362	0.040	<0.001
	Phase_A2	0.204	0.040	0.000
Approaching Vehicles	Veh_No		Reference	
	Veh_Yes	0.103	0.024	0.000
Type of pair × Site	Type_PairA:SiteCO		Reference	
	Type_PairB:SitePT	-0.180	0.064	0.005
	Type_PairC:SitePT	0.089	0.063	0.161
	ICC1		0.006	
	ICC2		0.032	
	AIC		3510.056	

5.3.3.1. Social factors

According to the model results, there was a statistically significant interaction between the type of pair of pedestrians and the study site regarding the average angle. Figure 78 illustrates that the angles of pedestrians were greater for type B pairs (triads) compared to type C pairs (triads) and type A pairs (dyads) in both study sites. Additionally, the figure indicates that there is less variation in angles for type A pairs compared to types B and C in both study sites. Furthermore, it is noteworthy that overall, the variation in angles is lower in Site CO for all three types of pairs.

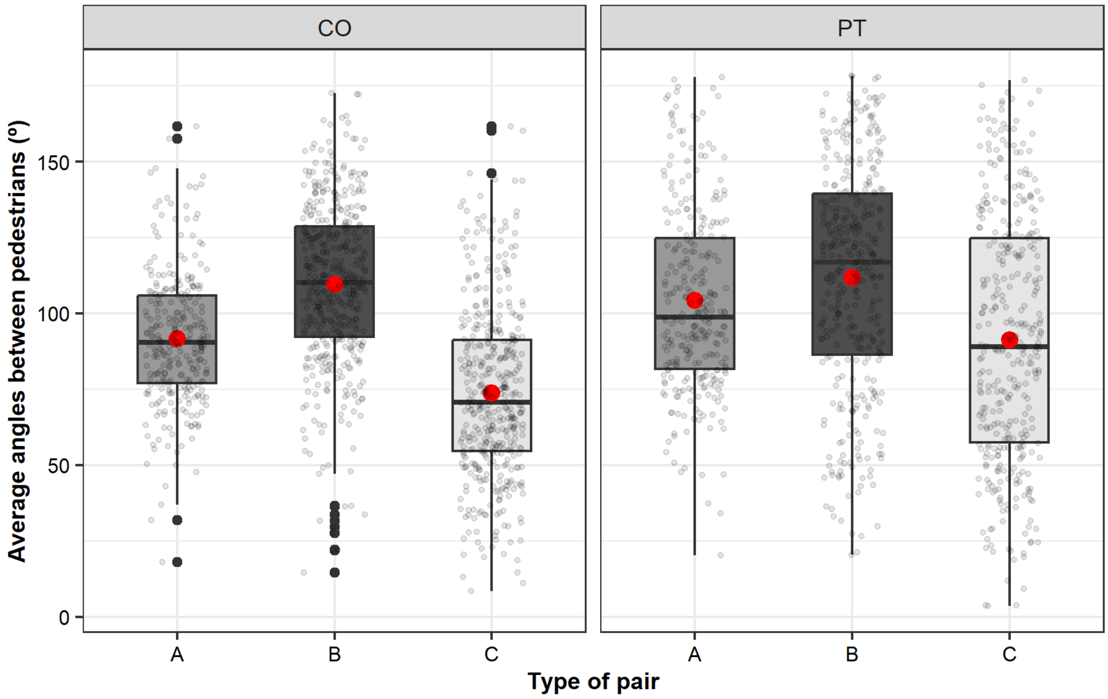


Figure 78. Boxplot of average angle of pedestrian pairs as a function of the type pair according to the study site.

Based on the contrast results comparing the type of pairs according to the study sites (Table 62), significant differences were observed in the average angles for all types of pairs in the CO site. However, in the PT site, the difference between type A and type B pairs was not statistically significant.

Table 62 – Contrasts of type of pairs according to the study site.

Type of pair	**CO**			**PT**		
	Estimate	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
A - B	-0.285	0.045	<.0001	-0.105	0.046	0.062
A - C	0.340	0.044	<.0001	0.251	0.047	<.0001
B - C	0.625	0.037	<.0001	0.356	0.040	<.0001

When comparing the model results between study sites for different types of pairs, significant differences were observed in type A ($\hat{\beta}$=-0.234, SE=0.063 p=<0.001) and type C ($\hat{\beta}$=-0.323, SE=0.054 p=<0.001). These results indicate that the average angles in Site CO were lower compared to the angles in Site PT for these types of pairs. However, for type B pairs, there was no significant difference ($\hat{\beta}$=–0.054, SE=0.054, p=0.325) between the two study sites.

5.3.3.2. External factors

Regarding external factors, the angles of pedestrians vary according to the crossing phase, as depicted in Figure 79. The average angle increases before the people cross the street (B2), decrease at the first segment during the road crossing (D1) but increase again in the second segment (D2). After the road crossing increase again in A1 but decrease at the end of the trajectory (A2). Particularly, there is less variation in angles in the segments during the road crossing (D1 and D2).

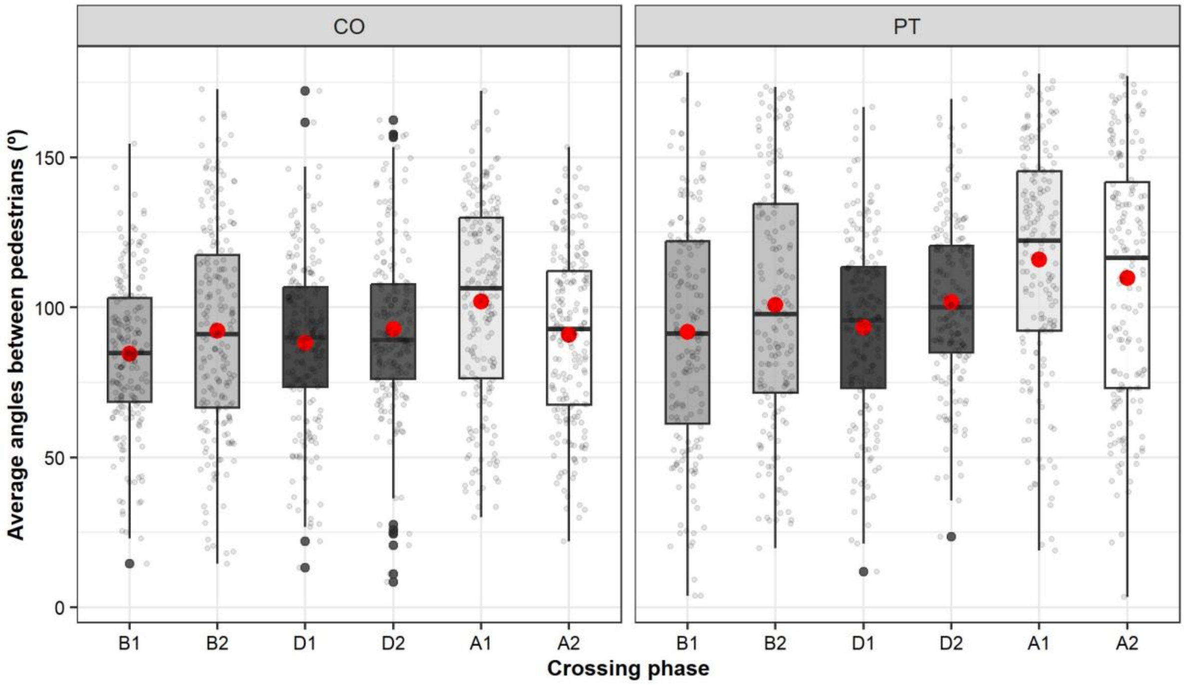


Figure 79. Boxplot of average angle of pedestrian pairs as a function of the crossing phase according to the study site.

According to the results of the model and the contrasts presented in Table 63, significant differences (p-value < 0.05) were observed between the segments in the crossing phase, except between B2-D1 and D1-D2. Additionally, there was a significant difference between the initial average angle (B1) and the final average angle (A2), with the final angle being greater. These findings indicate that the angles of pedestrians vary throughout the crossing phases, with the angles increasing before crossing, decreasing during the road crossing, and increasing again after crossing.

Table 63 – Contrasts results of the crossing phase.

Crossing phase	Estimate	SE	p-value
B1 - B2	-0.142	0.040	0.005
B2 - D1	0.097	0.040	0.139
D1 - D2	-0.112	0.040	0.054
D2 - A1	-0.205	0.040	<0.001
A1 - A2	0.159	0.040	0.001
B1 - A2	-0.204	0.040	<0.001

The angles between pairs of pedestrians were indeed affected by the presence of approaching vehicles, as depicted in Figure 80. When interactions with vehicles occurred, the angles increased. The results of the model also confirmed this observation, showing a significant difference ($\hat{\beta}$=0.103, SE=0.025, p-value <0.001) in the angles of pedestrians in the presence of approaching vehicles compared to situations without vehicles. This indicates that the presence of vehicles influences the spatial behavior of pedestrians, leading to larger angles between pairs of pedestrians.

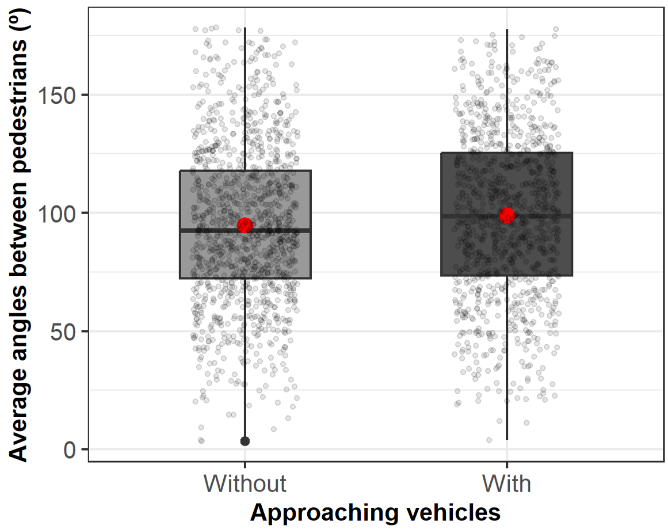


Figure 80. Boxplot of average angle of pedestrian pairs as a function of the presence of approaching vehicles according to the study site.

5.4. Discussion

The results presented in this chapter provide valuable insights into the complex dynamics of pedestrian movement, highlighting the influence of various parameters on pedestrian behavior, in different cultural contexts. Social factors, such as walking in a group, group size, and sex composition, have been shown to impact pedestrian movement patterns. Additionally, external and cultural factors, including the study site, crossing phases, and interactions with others, contribute to the intricate nature of pedestrian behavior.

One significant implication of this study is the need to enhance cultural sensitivity and adjust attitude campaigns aimed at promoting pedestrian safety. Examples from other countries support this conclusion. In the specific context of Turkey, improving the effectiveness of attitude campaigns could involve emphasizing the internalization of safety regulations among target groups. By highlighting the legitimacy and efficiency of these regulations, pedestrians are more likely to embrace and adhere to safe practices (Nordfjærn & Şimşekoğlu, 2013). Similarly, in Mexico, successful efforts have been made in educating pedestrians and cyclists. However, a shift in focus is now warranted towards enhancing driver education to ensure a comprehensive approach to road safety (Obregón-Biosca et al., 2018).

Adopting a culturally sensitive and context-specific approach to road safety campaigns is paramount in mitigating risks, reducing pedestrian accidents, and safeguarding the well-being of pedestrians in various cultural contexts. This approach recognizes the nuanced interplay between cultural norms, social dynamics, and external factors that shape pedestrian behavior. By thoroughly analyzing and recognizing these factors, transportation authorities and policymakers can tailor road safety initiatives to address the unique needs, attitudes, and behaviors of pedestrians in specific cultural contexts.

5.4.1. Social factors: group size and sex

Pedestrians' personal and social characteristics are essential in explaining their walking behavior. This study found significant differences in walking speeds based on group size and sex composition within each study site. Consistent with previous research, the average speed decreased as group size increased due to the cohesive effect that groups of pedestrians maintain to facilitate communication (Moussaïd et al., 2010; Willis et al., 2004) or to preserve group cohesion (Bandini et al., 2014).

Significant differences were observed based on the sex composition within each country, with male groups consistently exhibiting higher walking speeds than female groups. These findings are consistent with previous studies conducted by Costa (2010) and Willis et al. (2004), which also reported similar results. Thus, the current study supports and reinforces the existing literature on sex-related differences in walking speeds.

However, no significant differences in walking speeds were found based on group size or sex composition between the two study locations. This contrasts with previous research conducted by Bosina and Weidmann (2017), who reported significant variations in pedestrian speeds across different countries. Bosina and Weidmann (2017) acknowledged the challenge of attributing these differences solely to country-specific factors such as climate, wealth, or unobservable personal characteristics, which could influence walking speed.

The present study conducted experiments in two study locations on days with similar weather conditions. Therefore, it would be inappropriate to attribute the absence of observed speed differences to climatic factors. Further investigation is warranted to explore additional variables that may contribute to the observed results.

Regarding interpersonal distance, the study findings support the notion that females tend to maintain closer interpersonal distances while walking, consistent with Costa (2010) and Willis et al. (2004), which observed greater distances between individuals in all-male groups compared to all-female groups. Furthermore, differences in interpersonal distances were identified between the two study sites. The CO site exhibited smaller average distances in certain group compositions than the PT site. These results diverge from self-reported data collected by Sorokowska et al. (2017), who collected self-reported data through surveys asking participants to indicate their preferred distance with familiar individuals on a numeric scale. Sorokowska et al. (2017) found lower interpersonal distances with acquaintances in Portugal compared to Colombia and that women preferred greater distances in the presence of acquaintances.

It is important to note that the current study utilized experimental observations, offering a less subjective measure than self-reported data like that used by Sorokowska et al. (2017). However, it is important to consider that the sample size in the current study was limited to 60 individuals across two locations.

In addition, previous studies have attempted to classify cultures as either contact or non-contact based on interpersonal distance, with contact cultures generally exhibiting shorter distances. Southern European and Latin American cultures have been identified as contact cultures (Hall, 1966). However, this study's results demonstrate that even though the study sites are within these contact cultures, significant differences in interpersonal distances can exist, as evidenced by the smaller distances observed of pedestrians at the CO site (Table 64). Consequently, Thus, future research incorporating larger sample sizes and additional study sites is warranted to validate these findings.

Table 64 – Average distance between pedestrians for each group size.

Group size	Pair	(Moussaïd et al., 2010)		In this study			
		Low density		Site CO		Site PT	
		D (m)	SE	D (m)	SE	D (m)	SE
Dyads	P1 - P2 (A)	0.78	0.02	0.76	0.01	0.84	0.01
Triads	P1 - P2 (B)	0.79	0.05	0.77	0.01	0.89	0.01
	P2 - P3 (C)	0.81	0.10	0.74	0.01	0.89	0.01

The results of this study indicate that the sex composition of pedestrian groups does not significantly influence the average angles between pairs of pedestrians, in contrast to the findings by Costa (2010). Costa's (2010) study revealed that mixed dyads exhibited the lowest level of misalignment, male dyads showed the highest level, and female dyads displayed intermediate alignment. This pattern was also observed in triads, with greater alignment in female groups compared to mixed or male groups.

However, this study did find a significant effect of group size and pair type. Specifically, the average angles at site CO were similar to those found in previous studies by Moussaïd et al. (2010) and lower than those at site PT (Table 65). These results suggest a significant difference between the two study sites, indicating potentially greater alignment at site CO.

Table 65 – Average angles of pedestrians for each group size.

Group size	Pair	(Moussaïd et al., 2010)		In this study			
		Low density		Site CO		Site PT	
		A (º)	SE	A (º)	SE	A (º)	SE
Dyads	P1 - P2 (A)	89.8	1.12	91.537	1.269	103.604	1.819
Triads	P1 - P2 (B)	97.8	5.14	110.018	1.303	112.818	2.015
	P2 - P3 (C)	87.1	4.46	73.371	1.348	90.887	2.203

Regarding the spatial organization of triads, the arrangement at site CO closely resembled the V-like shape mentioned in previous studies (Costa, 2010; Federici et al., 2014; Moussaïd et al., 2010). The spatial organization of pedestrians at site PT did not differ significantly in V-like shape, although it was slightly more open.

The differences in spatial arrangement may be influenced by interpersonal distances, as discussed earlier. The greater distances observed at site PT compared to site CO may contribute to the more open spatial organization observed. Additionally, it is worth noting that previous studies have demonstrated the influence of city size and population density on pedestrian speed (Bosina & Weidmann, 2017). Thus, the smaller angles observed at site CO could also be influenced by cultural factors that encourage closer contact and a more closed spatial organization.

5.4.2. External factors: crossing phase, approaching vehicles and interactions with out-group pedestrians

The study findings highlight the significance of external factors in shaping pedestrian behavior, including crossing phases, oncoming vehicles, and interactions with other pedestrians. The informal rule in Colombia, where pedestrians yield to vehicles even when they have priority, influences the pedestrian speed and waiting behavior, leading to differences in walking behavior compared to other study site.

From the available literature any previous study has examined crossing phases comparing different study sites, highlighting the novelty and importance of this work findings. The analysis based on the crossing phases revealed significant differences in pedestrian walking speed between the six sections: B1 and B2 Before, D1 and D2 During, and A1 and A2 After the road crossing. The speed pattern according to the crossing phase was consistent at both study sites, independent of oncoming vehicles. A reduction in speed before the crossing followed by an increase during the crossing could be observed at both sites. These findings are consistent with Gorrini et al. (2018) results, which point to crossing behavior comprising three distinctive phases (approaching, appraising, and crossing phases).

Comparing the crossing phases between the two study sites, there were significant speed differences before the crossing (segment B2) when approaching vehicles were present. Specifically, the reduction in pedestrian speed at the CO site before the crossing was more significant than at the PT site. These disparities may be attributed to the informal rule prevailing in Colombia, leading pedestrians to slow down before the crossing due to the assumption that they must yield to vehicles.

As mentioned earlier, in Colombia, many road users are unaware of the meaning of a pedestrian crossing. Unlike Portugal, Colombia currently lacks design standards for pedestrian safety and investments to upgrade high-risk locations. Furthermore, the maximum urban speed limit for vehicles in Colombia is 80 km/h, whereas in Portugal, it is 50 km/h. This difference in speed limits can also impact pedestrians' perception of danger and compel them to further reduce their speed (WHO, 2018).

Additionally, the study reveals distinct interpersonal distance patterns between the two study sites during crossing phases. At the CO site, pedestrians tend to approach each other as they approach the crosswalk and maintain a small distance during the crossing. Conversely, at the PT site, pedestrians increase their distance during the approaching and crossing phases, taking advantage of their right of way and the availability of more space. The difference in interpersonal distance behavior suggests variations in perceived right of way and cultural norms regarding pedestrian crossings.

On the other hand, the study findings demonstrate a consistent pattern of angles according to the crossing phase in both study sites. Prior to crossing, the angles between individuals increase, indicating reduced alignment among people. During the crossing, the angles decrease, implying a more aligned spatial organization. Finally, at the end of the crossing, the angles increase again, with the final angle being greater than the initial angle of the trajectory. This pattern suggests that approaching vehicles influence the angles between individuals and contribute to reduced alignment, particularly before the crossing.

The examination of crossing phases based on interpersonal distance and angles is a unique contribution to the existing literature, which has predominantly focused on interpersonal distances on sidewalks or in crowded areas (Costa, 2010; Moussaïd et al., 2010; Willis et al., 2004). By investigating how interpersonal distances and angles change throughout the crossing process, this study offers valuable insights into the dynamic nature of pedestrian behavior and its relationship with the presence of approaching vehicles on the operational factors of pedestrians.

In addition, it was observed that interaction with other pedestrians did not significantly impact the distance between individuals. However, in groups of three pedestrians, a significant decrease in walking speed was observed when interacting with pedestrians outside their group. This decrease in speed could be attributed to the desire of pedestrian groups to maintain cohesion while walking, as previous studies have suggested (Bandini et al., 2014; Moussaïd et al., 2010).

5.5. Conclusion

The study findings suggest that social, external and cultural factors significantly influence pedestrian behavior, highlighting the importance of considering context-specific factors when analyzing walking behavior and social interactions. Specifically, the study identified differences in speed patterns and spatial arrangement, including interpersonal distances between pairs' pedestrians and angles of pedestrians. These results demonstrate the impact of local context and informal rules on pedestrian behavior. Acknowledging and addressing cultural nuances is essential when designing pedestrian-friendly infrastructure and policies to promote safe and sustainable transportation practices.

Efforts to improve pedestrian safety should involve a combination of formal education programs and informal interactions between road users and the road environment, such as public awareness campaigns and community engagement programs. By fostering a road safety culture and aligning interventions with the social norms of the target population, policymakers can effectively promote behavioral change and create safer road environments. It is essential to conduct further research to recognize better the complex interplay between cultural factors, individual differences, and environmental/external factors in pedestrian behavior.

Future research should investigate pedestrian behavior in various geographic and socioeconomic contexts to avoid overgeneralization, considering a range of locations. This will provide a more comprehensive identification of the factors influencing walking behavior and ensure that interventions and policies are tailored to specific regions and populations. While this study provides valuable information on external factors affecting the pedestrian walking speed and spatial organization, it should be noted that the observations were limited to specific streets in each country and may only partially represent pedestrian behavior in other regions.

CHAPTER 6

CONCLUSION

6.1. Final remarks

The main objective of this doctoral project was to study the behavior of pedestrians at road crossings, with a specific focus on isolated individuals and social groups in areas with low pedestrian density. The project aimed to address knowledge gaps, explore pedestrian behavior and movement patterns considering social interactions (such as group size and sex composition), and investigate the influence of external (such as crossing phases, approaching vehicles, and interactions with other pedestrians) and cultural factors (study site of different regions) on pedestrian behavior at road crossings. This doctoral thesis contributed to the existing knowledge on pedestrian behavior by examining and exploring these factors. The insights gained will aid in developing evidence-based strategies and interventions for designing urban spaces that enhance pedestrian safety, efficiency, and overall urban mobility.

The project consisted of three studies that addressed different aspects of social interaction in pedestrian movements. The first study focused on determining the typical size of social groups (Chapter 3). The second study explored the impact of social interactions on pedestrian behavior at three crosswalks within the same city (Chapter 4). In addition, the third study compared the effects of social interactions and external factors in two locations representing different cultures (Chapter 5).

While each chapter has its conclusion section, this part summarizes the key factors influencing pedestrian crossing behavior, specifically walking speed, distances, and angles. The final remarks highlight the main findings and implications derived from the research conducted throughout the thesis.

6.1.1. Social factors (Chapters 3 and 4)

Chapter 3 presents the results of an observational study on pedestrian counts, confirming that at least 35% of observed pedestrians walk in groups in residential areas. This percentage is even higher in school zones and nearby streets, reaching approximately 60%. In commercial zones, on average, 48% of people walk in social groups. These empirical observations have allowed for the identification of the most common group sizes, which are 2 and 3 people.

The findings related to social factors indicate that isolated individuals tend to walk at higher speeds than social groups, while larger groups are associated with decreased walking speeds. This decrease in speed can be attributed to the need for cohesion within the group and the facilitation of social interactions. Triads tend to have larger distances between individuals than dyads, possibly due to greater intimacy or different communication formations. Male groups walk faster and maintain greater distances between individuals than female groups. The spatial organization of groups does not differ based on group sex composition, but dyads tend to walk side by side, while triads exhibit a "V-like" formation (Chapter 4).

6.1.2. External factors (Chapter 4)

The analysis of external factors focused on crossing phases, interaction with approaching vehicles, parked vehicles, and out-group pedestrians. Pedestrians adjust their speed during different crossing phases and increase their distance from each other near the crosswalk when deciding whether to cross. Interestingly, the distance between pedestrians was smaller in broader zones, contrary to expectations based on crosswalk width.

The average angles between pedestrians were significantly lower in areas with wider sidewalks, suggesting that pedestrians prefer to walk side by side when provided sufficient space. During the crossing phase, which typically offers a broader and less obstructed area, there was less variation in angles compared to other phases. This indicates that walking directly in front of each other, as observed on narrow sidewalks, was uncommon. However, the angle at the beginning of the trajectory was smaller than at the end, indicating that angles varied according to the crossing phases. This suggests that the crossing phases influenced angle variation, potentially due to interaction with externalfactors and other pedestrians outside the group.

Regarding average speed, pedestrians exhibited a significant reduction before the road crossing, followed by an increase during the crossing and a subsequent reduction back to the initial speed. This pattern aligns with expectations, as pedestrians evaluate whether it is safe to cross before the crossing phase and reduce their speed during that assessment.

The study found that the average speed pattern varied according to group size, with singles having higher speeds and groups having lower speeds in all phases. However, there were differences in the pattern across phases based on the groups' sex. Before the road crossing, female groups showed a higher speed reduction than mixed and male groups. This phase was the only one where a significant difference was observed between females and mixed groups. Although the study did not specifically analyze the effect of sex on the decision-making process to cross, these differences suggest that sex plays a role in pedestrians' decision-making. The effect of oncoming vehicles was also significant in average speed based on sex composition but not group size.

The presence of parked vehicles near the crosswalk affects pedestrians' speed. Before the road crossing, the average speed of pedestrians decreased when there were parked vehicles, possibly due to reduced visibility and the need for caution. However, during the crossing, pedestrians increased their speed, potentially because the presence of parked vehicles provided a sense of safety by reducing the road width.

Furthermore, the presence of parked vehicles also influenced the average angle and distance between pedestrians. When parked vehicles were present, pedestrians tended to be closer to each other, and the angles between them decreased. This suggests that pedestrians may gather closer due to the difficulty of seeing approaching vehicles and collectively decide to proceed when they perceive it to be safe.

Triads and groups of women showed significant decreases in average speed when interacting with pedestrians outside their group, potentially to avoid separating from each other. There were no significant differences in the average distance between pedestrians, but the average angle increased slightly when interacting with pedestrians outside the group. This indicates that pedestrians adjust their speed in typical situations while the spatial organization remains unchanged. However, this effect may primarily impact triads as they occupy more space and aim to stay together.

6.1.3. Cultural factors (Chapter 5)

Examining cultural factors involved comparing data from study sites in different regions. While group size and sex effects on speed were consistent across study sites, differences were found in the distance between pairs of pedestrians and the angles of spatial organization. These differences can be associated with each study site's specific cultural norms and behaviors.

For instance, in the CO site, pedestrians follow an informal rule that prioritizes vehicles. As a result, pedestrians on this site tend to walk closer together. In contrast, people at the PT site increase their distances while crossing, possibly due to cultural norms prioritizing personal space or perception of safety.

Furthermore, the study found that in the CO site, people decrease their distances from each other while waiting to cross together. This suggests a cultural behavior where pedestrians prefer to wait and cross as a group rather than individually. In comparison, this behavior may be different in other study sites.

In general, the findings indicate that cultural factors significantly influence pedestrian behavior. The differences observed in the distance between pedestrians and the angles of spatial organization highlight the importance of considering context-specific factors when designing pedestrian-friendly infrastructure and policies. Cultural norms and behaviors should be considered to ensure that interventions are effective and aligned with the local context.

To improve pedestrian safety, it is recommended to implement formal education programs, public awareness campaigns, and community engagement initiatives aligned with social norms in each cultural context. Understanding and incorporating cultural factors into road safety campaigns can enhance their effectiveness and increase their potential impact.

Studying pedestrian behavior in various geographic and socioeconomic contexts is crucial to avoid overgeneralizing results. By doing so, researchers and policymakers can develop appropriate and tailored strategies for different populations, considering the specific cultural factors that shape pedestrian behavior in each context.

While this doctoral thesis provides valuable insights into pedestrian behavior, it is essential to acknowledge the study's limitations. One limitation is that the conclusions are based on young voluntary participants, which may introduce a bias and limit the generalizability of the findings. Further research should involve larger sample sizes and participants from different age groups to validate and generalize the results. This would provide a more representative understanding of pedestrian behavior across diverse demographics.

Another important aspect is exploring pedestrian behavior in diverse urban settings with varying infrastructure characteristics. Different cities and environments may have unique features that can impact pedestrian behavior, such as the presence of pedestrian-friendly infrastructure, traffic patterns, and cultural norms. Examining these factors in different contexts would ensure the applicability of the conclusions and enhance our understanding of pedestrian behavior in various settings.

In conclusion, this doctoral thesis significantly contributes to the understanding of pedestrian behavior at road crossings, particularly concerning social interaction, external factors, and cultural context. The findings highlight the importance of considering factors such as group size, sex composition, crossing phases, and interactions with vehicles and pedestrians in designing effective strategies for pedestrian safety and urban planning. However, it is essential to acknowledge the study's limitations, such as the reliance on young voluntary participants. Future research should continue to explore these factors and their implications in different contexts, enabling the development of evidence-based interventions and policies that promote enhanced pedestrian mobility and safety.

6.2. Future works

The findings of this doctoral thesis highlight the importance of including social interactions and the influence of individual, external, and cultural factors in exploring the complexities of pedestrian behavior. With the findings found in this doctoral thesis, it is possible to continue delving into the interrelationships to obtain valuable information that allows the development of more precise models, simulations, and interventions to improve pedestrian safety and urban planning strategies. The most relevant topics to be developed in the near future are presented below.

6.2.1. Incorporating the models into virtual experiments

- Future research should consider incorporating the collected data into virtual experiments. Virtual simulations can provide controlled environments where the behavior of pedestrians within social groups can be studied in detail. By integrating real-world data into virtual simulations, researchers can better understand how individuals interact with each other, with other pedestrians, and with different social groups in response to external stimuli.
- Virtual experiments can also allow for manipulating variables such as group size, composition, and spatial configurations, providing insights into how these factors influence pedestrian behavior during road crossings. By conducting virtual experiments with various scenarios, researchers can analyze the effects of different social dynamics on pedestrian movement patterns and dynamics, contributing to a more comprehensive understanding of social group behavior.
- Furthermore, incorporating data into virtual experiments can facilitate the exploration of novel interventions and design strategies to improve pedestrian safety and optimize pedestrian facilities. Researchers can test different scenarios and evaluate the impact of interventions such

as signage, traffic control measures, or changes in infrastructure on the behavior of pedestrians within social groups.

- One area of research could use the knowledge about the behavior of pedestrians in groups to help improve the accuracy and reliability of pedestrian detection algorithms used by automated vehicles. This would enable them to effectively identify and track pedestrians in various externalconditions, including urban settings with the presence of social groups.
- By combining real-world data with virtual experiments, researchers can bridge the gap between observational studies and controlled experiments, allowing for a deeper exploration of the complexities of pedestrian behavior and social interactions in urban environments.

6.2.2. Integration of collected data into microsimulation tools

- One direction of future research involves utilizing the collected data on pedestrian behavior, including the average walking speed, pedestrian organization, and crossing phase patterns, to calibrate and validate microsimulation models. The aim is to ensure that the models accurately represent pedestrian movements within social groups during road crossings by comparing the simulated behavior to observed real-world data. This process allows researchers to fine-tune the models and enhance their accuracy in capturing the dynamics and complexities of pedestrian behavior in social groups.
- Moreover, incorporating data on social interactions into microsimulation tools can further enhance the models' capabilities. By integrating information on how pedestrians interact with each other, the models can better capture the intricacies of social dynamics within groups. This enables a more precise representation of pedestrian behavior in social groups during road crossings.
- Incorporating real-world data into these models, researchers can enhance the accuracy and realism of the simulations, leading to more reliable predictions and insights into pedestrian behavior.

In addition to the previous points, future works should also consider the analysis of gait parameters in the study of pedestrian behavior, utilizing the collected data. Gait parameters refer to various measurements of how individuals walk, including stride length, step frequency, and cadence. These parameters provide valuable insights into the kinematics and dynamics of pedestrian movement.

- By analyzing gait parameters, researchers can further understand how social interactions and other factors influence pedestrian behavior. For example, the study could examine how different group sizes or compositions affect stride length and step frequency within social groups. This analysis can provide insights into how pedestrians adjust their walking patterns when walking in close to others.
- Moreover, studying gait parameters can help identify variations in walking behavior among different demographic groups. For instance, researchers can analyze how age, sex, or physical capabilities (e.g., individuals with disabilities) influence gait parameters during pedestrian crossings. This information is crucial for designing inclusive and accessible urban environments.
- Another important aspect is to analyze how the gait parameters vary according to the crossing phases. By examining gait parameters during different phases, such as before, during, and after crossing, researchers can identify factors influencing pedestrian behavior in risk perception and crossing decisions in vehicle interactions.

6.2.3. Additional considerations

Future studies should consider mixed traffic conditions, including particular types of pedestrians, such as people with disabilities (e.g., wheelchair users).

The coexistence of pedestrians and micro-mobility vehicles (MMVs) presents a recent challenge to road infrastructure's efficient and safe use. MMVs, such as bicycles and electric scooters, are becoming more popular and widely used, potentially due to the time savings they offer for short distances to their final destinations. MMVs can move at higher speeds, affecting pedestrians' risk perception. Furthermore, the effect of MMV interaction on the behavior of pedestrians in social groups and the operational efficiency of shared spaces remains unknown. Thus, it is necessary to examine these interactions in future studies.

REFERENCES

Agencia Nacional de Seguridad Vial. (2021). *Informe de Resultados de la Encuesta Territorial de Comportamiento en Seguridad Vial (ETCSV)*.

Aghabayk, K., Esmailpour, J., Jafari, A., & Shiwakoti, N. (2021). Observational-based study to explore pedestrian crossing behaviors at signalized and unsignalized crosswalks. *Accident Analysis & Prevention*, *151*, 105990. https://doi.org/https://doi.org/10.1016/j.aap.2021.105990

Alhajyaseen, W. K. M., & Iryo-Asano, M. (2017). Studying critical pedestrian behavioral changes for the safety assessment at signalized crosswalks. *Safety Science*, *91*, 351–360. https://doi.org/https://doi.org/10.1016/j.ssci.2016.09.002

Arellana, J., Saltarín, M., Larrañaga, A. M., Alvarez, V., & Henao, C. A. (2020). Urban walkability considering pedestrians' perceptions of the built environment: a 10-year review and a case study in a medium-sized city in Latin America. *Transport Reviews*, *40*(*2*), 183–203. https://doi.org/10.1080/01441647.2019.1703842

Askarizad, R., & Safari, H. (2020). The influence of social interactions on the behavioral patterns of the people in urban spaces (case study: The pedestrian zone of Rasht Municipality Square, Iran). *Cities*, *101*, 102687. https://doi.org/https://doi.org/10.1016/j.cities.2020.102687

Aveni, A. F. (1977). The Not-So-Lonely Crowd: Friendship Groups in Collective Behavior. *Sociometry*, *40*(*1*), 96. https://doi.org/10.2307/3033551

Baker, G., Pillinger, R., Kelly, P., & Whyte, B. (2021). Quantifying the health and economic benefits of active commuting in scotland. *Journal of Transport & Health*, *22*, 101111. https://doi.org/https://doi.org/10.1016/j.jth.2021.101111

Bandini, S., Gorrini, A., & Vizzari, G. (2014). Towards an integrated approach to crowd analysis and crowd synthesis: A case study and first results. *Pattern Recognition Letters*, *44*, 16–29. https://doi.org/https://doi.org/10.1016/j.patrec.2013.10.003

Bernhoft, I. M., & Carstensen, G. (2008). Preferences and behaviour of pedestrians and cyclists by age and gender. *Transportation Research Part F: Traffic Psychology and Behaviour*, *11*(*2*), 83–95. https://doi.org/http://dx.doi.org/10.1016/j.trf.2007.08.004

Blue, V. J., & Adler, J. L. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways. *Transportation Research Part B: Methodological*, *35*(*3*), 293–312. https://doi.org/https://doi.org/10.1016/S0191-2615(99)00052-1

Bosina, E., & Weidmann, U. (2017). Estimating pedestrian speed using aggregated literature data.

Physica A: Statistical Mechanics and Its Applications, *468*, 1–29. https://doi.org/https://doi.org/10.1016/j.physa.2016.09.044

Bulla-Cruz, L. A., Laureshyn, A., & Lyons, L. (2020). Event-based road safety assessment: A novel approach towards risk microsimulation in roundabouts. *Measurement*, *165*, 108192. https://doi.org/https://doi.org/10.1016/j.measurement.2020.108192

Cambon de Lavalette, B., Tijus, C., Poitrenaud, S., Leproux, C., Bergeron, J., & Thouez, J. P. (2009). Pedestrian crossing decision-making: A situational and behavioral approach. *Safety Science*, *47*(*9*), 1248–1253. https://doi.org/10.1016/j.ssci.2009.03.016

Cavill, N., Kahlmeier, S., Rutter, H., Racioppi, F., & Oja, P. (2008). Economic analyses of transport infrastructure and policies including health effects related to cycling and walking: A systematic review. *Transport Policy*, *15*(*5*), 291–304. https://doi.org/https://doi.org/10.1016/j.tranpol.2008.11.001

Chattaraj, U., Seyfried, A., & Chakroborty, P. (2009). Comparision of pedestrian fundamental diagram across cultures. *Advances in Complex Systems*, *12*(*03*), 393–405. https://doi.org/10.1142/S0219525909002209

Coleman, J. S., & James, J. (1961). The Equilibrium Size Distribution of Freely-Forming Groups. *Sociometry*, *24*(*1*), 36–45. https://doi.org/10.2307/2785927

Costa, M. (2010). Interpersonal distances in group walking. *Journal of Nonverbal Behavior*, *34*(*1*), 15–26. https://doi.org/10.1007/s10919-009-0077-y

D'Orazio, M., Spalazzi, L., Quagliarini, E., & Bernardini, G. (2014). Agent-based model for earthquake pedestrians' evacuation in urban outdoor scenarios: Behavioural patterns definition and evacuation paths choice. *Safety Science*, *62*, 450–465. https://doi.org/https://doi.org/10.1016/j.ssci.2013.09.014

Delclòs-Alió, X., Rodríguez, D. A., Medina, C., Miranda, J. J., Avila-Palencia, I., Targa, F., Moran, M. R., Sarmiento, O. L., & Quistberg, D. A. (2022). Walking for transportation in large Latin American cities: walking-only trips and total walking events and their sociodemographic correlates. *Transport Reviews*, *42*(*3*), 296–317. https://doi.org/10.1080/01441647.2021.1966552

Díaz, E. (2002). Theory of planned behavior and pedestrians' intentions to violate traffic regulations. *Transportation Research Part F: Traffic Psychology and Behaviour*, *5*(*3*), 169–175. https://doi.org/10.1016/S1369-8478(02)00015-3

Dissanayake, D., Aryaija, J., & Wedagama, D. M. P. (2009). Modelling the effects of land use and temporal factors on child pedestrian casualties. *Accident Analysis and Prevention*, *41*(*5*), 1016–1024.

https://doi.org/10.1016/j.aap.2009.06.015

Do, T., Haghani, M., & Sarvi, M. (2016). Group and Single Pedestrian Behavior in Crowd Dynamics. *Transportation Research Record*, *2540*(*1*), 13–19. https://doi.org/10.3141/2540-02

Dommes, A., & Cavallo, V. (2011). The role of perceptual, cognitive, and motor abilities in street-crossing decisions of young and older pedestrians. *Ophthalmic and Physiological Optics*, *31*(*3*), 292–301. https://doi.org/https://doi.org/10.1111/j.1475-1313.2011.00835.x

Dommes, A., Granié, M.-A., Cloutier, M.-S., Coquelet, C., & Huguenin-Richard, F. (2015). Red light violations by adult pedestrians and other safety-related behaviors at signalized crosswalks. *Accident Analysis & Prevention*, *80*, 67–75. https://doi.org/https://doi.org/10.1016/j.aap.2015.04.002

Evans, D., & Norman, P. (1998). Understanding pedestrians' road crossing decisions: an application of the theory of planned behaviour. *Health Education Research*, *13*(*4*), 481–489. https://doi.org/10.1093/her/13.4.481-a

Faria, J. J., Krause, S., & Krause, J. (2010). Collective behavior in road crossing pedestrians: the role of social information. *Behavioral Ecology*, *21*(*6*), 1236–1242. https://doi.org/10.1093/beheco/arq141

Federici, M. L., Gorrini, A., Manenti, L., & Vizzari, G. (2014). *An Innovative Scenario for Pedestrian Data Collection: The Observation of an Admission Test at the University of Milano-Bicocca BT - Pedestrian and Evacuation Dynamics 2012* (U. Weidmann, U. Kirsch, & M. Schreckenberg (eds.); pp. 143–150). Springer International Publishing.

Feng, Y., Duives, D., Daamen, W., & Hoogendoorn, S. (2021). Data collection methods for studying pedestrian behaviour: A systematic review. *Building and Environment*, *187*, 107329. https://doi.org/https://doi.org/10.1016/j.buildenv.2020.107329

Fonseca, F., Ribeiro, P., Jabbari, M., Petrova, E., Papageorgiou, G., Conticelli, E., Tondelli, S., & Ramos, R. (2020). *Smart Pedestrian Network: An Integrated Conceptual Model for Improving Walkability BT - Society with Future: Smart and Liveable Cities* (P. Pereira, R. Ribeiro, I. Oliveira, & P. Novais (eds.); pp. 125–142). Springer International Publishing.

Fu, L., Cao, S., Shi, Y., Chen, S., Yang, P., & Fang, J. (2019). Walking behavior of pedestrian social groups on stairs: A field study. *Safety Science*, *117*, 447–457. https://doi.org/10.1016/j.ssci.2019.04.048

Fu, T., Hu, W., Miranda-Moreno, L., & Saunier, N. (2019). Investigating secondary pedestrian-vehicle interactions at non-signalized intersections using vision-based trajectory data. *Transportation Research Part C: Emerging Technologies*, *105*, 222–240.

https://doi.org/https://doi.org/10.1016/j.trc.2019.06.001

Fu, T., Miranda-Moreno, L., & Saunier, N. (2018). A novel framework to evaluate pedestrian safety at non-signalized locations. *Accident Analysis & Prevention*, *111*, 23–33. https://doi.org/https://doi.org/10.1016/j.aap.2017.11.015

Gorrini, A., Bandini, S., & Sarvi, M. (2014). Group Dynamics in Pedestrian Crowds. *Transportation Research Record: Journal of the Transportation Research Board*, *2421*(*1*), 51–56. https://doi.org/10.3141/2421-06

Gorrini, A., Crociani, L., Vizzari, G., & Bandini, S. (2018). Observation results on pedestrian-vehicle interactions at non-signalized intersections towards simulation. *Transportation Research Part F: Traffic Psychology and Behaviour*, *59*, 269–285. https://doi.org/https://doi.org/10.1016/j.trf.2018.09.016

Granié, M. A., Brenac, T., Montel, M. C., Coquelet, C., Millot, M., Monti, F., & Pannetier, M. (2013). Qualitative analysis of pedestrians' perception of the urban environment when crossing streets. *Advances in Transportation Studies*, *31*, 17–34. https://doi.org/10.4399/97888548663242

Granié, M. A., Brenac, T., Montel, M. C., Millot, M., & Coquelet, C. (2014). Influence of built environment on pedestrian's crossing decision. *Accident Analysis and Prevention*, *67*, 75–85. https://doi.org/10.1016/j.aap.2014.02.008

Guo, Z., & Loo, B. P. Y. (2013). Pedestrian environment and route choice: evidence from New York City and Hong Kong. *Journal of Transport Geography*, *28*, 124–136. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2012.11.013

Hall, E. T. (1966). *The hidden dimension* (Vol. 609). Anchor.

Helbing, D., Farkas, I. J., Molnar, P., & Vicsek, T. (2002). Simulation of pedestrian crowds in normal and evacuation situations. *Pedestrian and Evacuation Dynamics*, *21*(*2*), 21–58.

Hofstede, G. (1980). Culture and Organizations. *International Studies of Management & Organization*, *10*(*4*), 15–41. https://doi.org/10.1080/00208825.1980.11656300

Holland, C., & Hill, R. (2007). The effect of age, gender and driver status on pedestrians' intentions to cross the road in risky situations. *Accident Analysis & Prevention*, *39*(*2*), 224–237. https://doi.org/https://doi.org/10.1016/j.aap.2006.07.003

Hooftman, N., Messagie, M., Van Mierlo, J., & Coosemans, T. (2018). A review of the European passenger car regulations – Real driving emissions vs local air quality. *Renewable and Sustainable Energy Reviews*, *86*, 1–21. https://doi.org/https://doi.org/10.1016/j.rser.2018.01.012

Hoogendoorn, S. P., & Bovy, P. H. L. (2004). Pedestrian route-choice and activity scheduling theory and models. *Transportation Research Part B: Methodological*, *38*(*2*), 169–190. https://doi.org/https://doi.org/10.1016/S0191-2615(03)00007-9

Hu, Y., Zhang, J., Xiao, H., Cao, S., Ren, X., Liang, X., Li, H., & Song, W. (2020). Experimental study and analysis on behaviours and strategies of social groups and individuals. *Safety Science*, *127*. https://doi.org/10.1016/j.ssci.2020.104736

Hussein, M., & Sayed, T. (2015). Microscopic Pedestrian Interaction Behavior Analysis Using Gait Parameters. *Transportation Research Record*, *2519*(*1*), 28–38. https://doi.org/10.3141/2519-04

IDEAM. (2019). *Boletín Climatológico de diciembre de 2019*.

IPMA. (2019). *Boletim climático de Junho e Julho de 2019*.

Ishaque, M. M., & Noland, R. B. (2008). Behavioural Issues in Pedestrian Speed Choice and Street Crossing Behaviour: A Review. *Transport Reviews*, *28*(*1*), 61–85. https://doi.org/10.1080/01441640701365239

Issartel, J., Marin, L., & Cadopi, M. (2007). Unintended interpersonal co-ordination: "can we march to the beat of our own drum?" *Neuroscience Letters*, *411*(*3*), 174–179. https://doi.org/https://doi.org/10.1016/j.neulet.2006.09.086

Johnsson, C., Laureshyn, A., & Dágostino, C. (2021). A relative approach to the validation of surrogate measures of safety. *Accident Analysis & Prevention*, *161*, 106350. https://doi.org/https://doi.org/10.1016/j.aap.2021.106350

Johnsson, C., Norén, H., & Laureshyn, A. (2018a). T-Analyst - semi-automated tool for traffic conflict analysis. *InDeV, Horizon 2020 Project*, *Deliverabl*.

Johnsson, C., Norén, H., & Laureshyn, A. (2018b). T-Analyst - semi-automated tool for traffic conflict analysis. In *InDeV, Horizon 2020 project*.

Karamouzas, I., & Overmars, M. (2012). Simulating and Evaluating the Local Behavior of Small Pedestrian Groups. *IEEE Transactions on Visualization and Computer Graphics*, *18*(*3*), 394–406. https://doi.org/10.1109/TVCG.2011.133

Kircher, K., Eriksson, O., Forsman, Å., Vadeby, A., & Ahlstrom, C. (2017). Design and analysis of semi-controlled studies. *Transportation Research Part F: Traffic Psychology and Behaviour*, *46*, 404–412. https://doi.org/http://dx.doi.org/10.1016/j.trf.2016.06.016

Lian, L., Mai, X., Song, W., Richard, Y. K. K., Rui, Y., & Jin, S. (2017). Pedestrian merging behavior analysis: An experimental study. *Fire Safety Journal*, *91*, 918–925. https://doi.org/https://doi.org/10.1016/j.firesaf.2017.04.015

Liao, W., Seyfried, A., Zhang, J., Boltes, M., Zheng, X., & Zhao, Y. (2014). Experimental Study on

Pedestrian Flow through Wide Bottleneck. *Transportation Research Procedia*, *2*, 26–33. https://doi.org/https://doi.org/10.1016/j.trpro.2014.09.005

Liu, Y.-C., & Tung, Y.-C. (2014). Risk analysis of pedestrians' road-crossing decisions: Effects of age, time gap, time of day, and vehicle speed. *Safety Science*, *63*, 77–82. https://doi.org/10.1016/j.ssci.2013.11.002

Lu, L., Chan, C.-Y., Wang, J., & Wang, W. (2017). A study of pedestrian group behaviors in crowd evacuation based on an extended floor field cellular automaton model. *Transportation Research Part C: Emerging Technologies*, *81*, 317–329. https://doi.org/https://doi.org/10.1016/j.trc.2016.08.018

Lund, I. O., & Rundmo, T. (2009). Cross-cultural comparisons of traffic safety, risk perception, attitudes and behaviour. *Safety Science*, *47*(*4*), 547–553. https://doi.org/https://doi.org/10.1016/j.ssci.2008.07.008

Martin, A. (2006). *Factors influencing pedestrian safety: a literature review*. TRL.

Matsumoto, D. (2007). Culture, Context, and Behavior. *Journal of Personality*, *75*(*6*), 1285–1320. https://doi.org/https://doi.org/10.1111/j.1467-6494.2007.00476.x

McNeish, D. (2016). On Using Bayesian Methods to Address Small Sample Problems. *Structural Equation Modeling: A Multidisciplinary Journal*, *23*(*5*), 750–773. https://doi.org/10.1080/10705511.2016.1186549

Melnikov, V. R., Christopoulos, G. I., Krzhizhanovskaya, V. V, Lees, M. H., & Sloot, P. M. A. (2022). Behavioural thermal regulation explains pedestrian path choices in hot urban environments. *Scientific Reports*, *12*(*1*), 2441. https://doi.org/10.1038/s41598-022-06383-5

Monsalves, M. J., Bangdiwala, A. S., Thabane, A., & Bangdiwala, S. I. (2020). LEVEL (Logical Explanations & Visualizations of Estimates in Linear mixed models): recommendations for reporting multilevel data and analyses. *BMC Medical Research Methodology*, *20*(*1*), 1–9. https://doi.org/https://doi.org/10.1186/s12874-019-0876-8

Montufar, J., Arango, J., Porter, M., & Nakagawa, S. (2007). Pedestrians' Normal Walking Speed and Speed When Crossing a Street. *Transportation Research Record*, *2002*(*1*), 90–97. https://doi.org/10.3141/2002-12

Moussaïd, M., Helbing, D., Garnier, S., Johansson, A., Combe, M., & Theraulaz, G. (2009). Experimental study of the behavioural mechanisms underlying self-organization in human crowds. *Proceedings of the Royal Society B: Biological Sciences*, *276*(*1668*), 2755–2762. https://doi.org/10.1098/rspb.2009.0405

Moussaïd, M., Perozo, N., Garnier, S., Helbing, D., & Theraulaz, G. (2010). The walking behaviour of pedestrian social groups and its impact on crowd dynamics. *PLoS ONE*, *5*(*4*). https://doi.org/10.1371/journal.pone.0010047

Nanaki, E. A., Koroneos, C. J., Roset, J., Susca, T., Christensen, T. H., De Gregorio Hurtado, S., Rybka, A., Kopitovic, J., Heidrich, O., & López-Jiménez, P. A. (2017). Environmental assessment of 9 European public bus transportation systems. *Sustainable Cities and Society*, *28*, 42–52. https://doi.org/https://doi.org/10.1016/j.scs.2016.08.025

Nessler, J. A., & Gilliland, S. J. (2009). Interpersonal synchronization during side by side treadmill walking is influenced by leg length differential and altered sensory feedback. *Human Movement Science*, *28*(*6*), 772–785. https://doi.org/https://doi.org/10.1016/j.humov.2009.04.007

Nordfjærn, T., & Şimşekoğlu, Ö. (2013). The role of cultural factors and attitudes for pedestrian behaviour in an urban Turkish sample. *Transportation Research Part F: Traffic Psychology and Behaviour*, *21*, 181–193. https://doi.org/https://doi.org/10.1016/j.trf.2013.09.015

Nordfjærn, T., Şimşekoğlu, Ö., & Rundmo, T. (2014). Culture related to road traffic safety: A comparison of eight countries using two conceptualizations of culture. *Accident Analysis & Prevention*, *62*, 319–328. https://doi.org/https://doi.org/10.1016/j.aap.2013.10.018

Obregón-Biosca, S. A., Betanzo-Quezada, E., Romero-Navarrete, J. A., & Ríos-Nuñez, M. (2018). Rating road traffic education. *Transportation Research Part F: Traffic Psychology and Behaviour*, *56*, 33–45. https://doi.org/https://doi.org/10.1016/j.trf.2018.03.033

Pan, X., Han, C. S., Dauber, K., & Law, K. H. (2006). Human and social behavior in computational modeling and analysis of egress. *Automation in Construction*, *15*(*4*), 448–461. https://doi.org/https://doi.org/10.1016/j.autcon.2005.06.006

Papadimitriou, E., Lassarre, S., & Yannis, G. (2017). Human factors of pedestrian walking and crossing behaviour. *Transportation Research Procedia*, *25*, 2002–2015. https://doi.org/https://doi.org/10.1016/j.trpro.2017.05.396

Papadimitriou, E., Yannis, G., & Golias, J. (2009). A critical assessment of pedestrian behaviour models. *Transportation Research Part F: Traffic Psychology and Behaviour*, *12*(*3*), 242–255. https://doi.org/http://dx.doi.org/10.1016/j.trf.2008.12.004

Papadimitriou, E., Yannis, G., & Golias, J. (2010). Theoretical Framework for Modeling Pedestrians' Crossing Behavior along a Trip. *Journal of Transportation Engineering*, *136*(*10*), 914–924. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000163

Parisi, D. R., Gilman, M., & Moldovan, H. (2009). A modification of the Social Force Model can reproduce experimental data of pedestrian flows in normal conditions. *Physica A: Statistical Mechanics and Its Applications*, *388*(*17*), 3600–3608. https://doi.org/https://doi.org/10.1016/j.physa.2009.05.027

Pelé, M., Bellut, C., Debergue, E., Gauvin, C., Jeanneret, A., Leclere, T., Nicolas, L., Pontier, F., Zausa, D., & Sueur, C. (2017). Cultural influence of social information use in pedestrian road-crossing behaviours. *Royal Society Open Science*, *4*(*2*), 160739. https://doi.org/10.1098/rsos.160739

Pinheiro, J. C., & Bates, D. M. (2000). *Linear Mixed-Effects Models: Basic Concepts and Examples BT - Mixed-Effects Models in S and S-PLUS* (pp. 3–56). Springer New York. https://doi.org/10.1007/0-387-22747-4_1

Pokorny, P., Skender, B., Bjørnskau, T., & Hagenzieker, M. P. (2021). Video observation of encounters between the automated shuttles and other traffic participants along an approach to right-hand priority T-intersection. *European Transport Research Review*, *13*(*1*), 59. https://doi.org/10.1186/s12544-021-00518-x

R Core Team. (2021). *R: A Language and Environment for Statistical Computing*. https://www.r-project.org/

Rajat, R., Ilango, T., & Satish, C. (2011). Design Implications of Walking Speed for Pedestrian Facilities. *Journal of Transportation Engineering*, *137*(*10*), 687–696. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000251

Remland, M. S., Jones, T. S., & Brinkman, H. (1995). Interpersonal distance, body orientation, and touch: effects of culture, gender, and age. *The Journal of Social Psychology*, *135*(*3*), 281–297. https://doi.org/10.1080/00224545.1995.9713958

Robin, T., Antonini, G., Bierlaire, M., & Cruz, J. (2009). Specification, estimation and validation of a pedestrian walking behavior model. *Transportation Research Part B: Methodological*, *43*(*1*), 36–56. https://doi.org/https://doi.org/10.1016/j.trb.2008.06.010

Rojas, F., Tarnogol, F., & Yang, H. S. (2016). Dynamic social formations of pedestrian groups navigating and using public transportation in a virtual city. *The Visual Computer*, *32*(*3*), 335–345. https://doi.org/10.1007/s00371-015-1187-7

Rosenbloom, T. (2009). Crossing at a red light: Behaviour of individuals and groups. *Transportation Research Part F: Traffic Psychology and Behaviour*, *12*(*5*), 389–394. https://doi.org/10.1016/j.trf.2009.05.002

Rosenbloom, T., Shahar, A., & Perlman, A. (2008). Compliance of Ultra-Orthodox and secular pedestrians with traffic lights in Ultra-Orthodox and secular locations. *Accident Analysis & Prevention*, *40*(*6*), 1919–1924. https://doi.org/https://doi.org/10.1016/j.aap.2008.08.004

Rutten, P., Lees, M. H., Klous, S., & Sloot, P. M. A. (2021). State-space models reveal bursty movement behaviour of dance event visitors. *EPJ Data Science*, *10*(*1*), 35. https://doi.org/10.1140/epjds/s13688-021-00292-9

Sebanz, N., Knoblich, G., & Prinz, W. (2003). Representing others' actions: just like one's own? *Cognition*, *88*(*3*), B11–B21. https://doi.org/https://doi.org/10.1016/S0010-0277(03)00043-X

Secretaria Distrital de Movilidad. (2019). *Encuesta de percepción de riesgo vial en la ciudad de Bogota*.

Seyfried, A., Steffen, B., Klingsch, W., & Boltes, M. (2005). The fundamental diagram of pedestrian movement revisited. *Journal of Statistical Mechanics: Theory and Experiment*, *2005*(*10*), P10002. https://doi.org/10.1088/1742-5468/2005/10/P10002

Shao, J., Loy, C. C., & Wang, X. (2014). Scene-Independent Group Profiling in Crowd. *2014 IEEE Conference on Computer Vision and Pattern Recognition*, 2227–2234. https://doi.org/10.1109/CVPR.2014.285

Sheykhfard, A., Haghighi, F., Papadimitriou, E., & Van Gelder, P. (2021). Review and assessment of different perspectives of vehicle-pedestrian conflicts and crashes: Passive and active analysis approaches. *Journal of Traffic and Transportation Engineering (English Edition)*, *8*(*5*), 681–702. https://doi.org/https://doi.org/10.1016/j.jtte.2021.08.001

Shi, X., Ye, Z., Shiwakoti, N., & Grembek, O. (2018). A State-of-the-Art Review on Empirical Data Collection for External Governed Pedestrians Complex Movement. *Journal of Advanced Transportation*, *2018*, 1063043. https://doi.org/10.1155/2018/1063043

Singh, H., Arter, R., Dodd, L., Langston, P., Lester, E., & Drury, J. (2009). Modelling subgroup behaviour in crowd dynamics DEM simulation. *Applied Mathematical Modelling*, *33*(*12*), 4408–4423. https://doi.org/https://doi.org/10.1016/j.apm.2009.03.020

Singh, S. G., & Kumar, S. V. (2021). Dealing with Multicollinearity Problem in Analysis of Side Friction Characteristics Under Urban Heterogeneous Traffic Conditions. *Arabian Journal for Science and Engineering*, *46*(*11*), 10739–10755. https://doi.org/10.1007/s13369-020-05213-y

Smid, S. C., McNeish, D., Miočević, M., & van de Schoot, R. (2020). Bayesian Versus Frequentist Estimation for Structural Equation Models in Small Sample Contexts: A Systematic Review. *Structural Equation Modeling: A Multidisciplinary Journal*, *27*(*1*), 131–161. https://doi.org/10.1080/10705511.2019.1577140

Soares, F., Silva, E., Pereira, F., Silva, C., Sousa, E., & Freitas, E. (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. https://doi.org/https://doi.org/10.1016/j.trf.2021.08.014

Solmaz, B., Moore, B. E., & Shah, M. (2012). Identifying Behaviors in Crowd Scenes Using Stability Analysis for Dynamical Systems. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *34*(*10*), 2064–2070. https://doi.org/10.1109/TPAMI.2012.123

Sorokowska, A., Sorokowski, P., Hilpert, P., Cantarero, K., Frackowiak, T., Ahmadi, K., Alghraibeh, A. M., Aryeetey, R., Bertoni, A., Bettache, K., Blumen, S., Błażejewska, M., Bortolini, T., Butovskaya, M., Castro, F. N., Cetinkaya, H., Cunha, D., David, D., David, O. A., ... Pierce, J. D. (2017). Preferred Interpersonal Distances: A Global Comparison. *Journal of Cross-Cultural Psychology*, *48*(*4*), 577–592. https://doi.org/10.1177/0022022117698039

Sueur, C., Class, B., Hamm, C., Meyer, X., & Pelé, M. (2013). Different risk thresholds in pedestrian road crossing behaviour: A comparison of French and Japanese approaches. *Accident Analysis & Prevention*, *58*, 59–63. https://doi.org/http://dx.doi.org/10.1016/j.aap.2013.04.027

Teknomo, K. (2006). Application of microscopic pedestrian simulation model. *Transportation Research Part F: Traffic Psychology and Behaviour*, *9*(*1*), 15–27. https://doi.org/https://doi.org/10.1016/j.trf.2005.08.006

The, T. R. B. of, & Academies, N. (2010). *Highway Capacity Manual*.

Tsai, R. (1987). A versatile camera calibration technique for high-accuracy 3D machine vision metrology using off-the-shelf TV cameras and lenses. *IEEE Journal on Robotics and Automation*, *3*(*4*), 323–344. https://doi.org/10.1109/JRA.1987.1087109

United Nations. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. https://sdgs.un.org/2030agenda

Uzondu, C., Jamson, S., & Hibberd, D. (2020). Can infrastructure improvements mitigate unsafe traffic safety culture: A driving simulator study exploring cross cultural differences. *Transportation Research Part F: Traffic Psychology and Behaviour*, *73*, 205–221. https://doi.org/https://doi.org/10.1016/j.trf.2020.06.022

Uzzell, D., & Horne, N. (2006). The influence of biological sex, sexuality and gender role on interpersonal distance. *The British Journal of Social Psychology*, *45*(*Pt 3*), 579–597. https://doi.org/10.1348/014466605X58384

Vanumu, L. D., Ramachandra Rao, K., & Tiwari, G. (2017). Fundamental diagrams of pedestrian flow characteristics: A review. *European Transport Research Review*, *9*(*4*), 49. https://doi.org/10.1007/s12544-017-0264-6

Wainwright, P. E., Leatherdale, S. T., & Dubin, J. A. (2007). Advantages of mixed effects models over traditional ANOVA models in developmental studies: A worked example in a mouse model of fetal alcohol syndrome. *Developmental Psychobiology*, *49*(*7*), 664–674. https://doi.org/https://doi.org/10.1002/dev.20245

Wang, W., Zhang, J., Li, H., & Xie, Q. (2020). Experimental study on unidirectional pedestrian flows in a corridor with a fixed obstacle and a temporary obstacle. *Physica A: Statistical Mechanics and Its Applications*, *560*, 125188. https://doi.org/https://doi.org/10.1016/j.physa.2020.125188

Wedagama, P., Bird, R. N., & Metcalfe, A. V. (2006). The influence of urban land-use on non-motorised transport casualties. *Accident Analysis and Prevention*, *38*(*6*), 1049–1057. https://doi.org/10.1016/j.aap.2006.01.006

Weifeng, F., Lizhong, Y., & Weicheng, F. (2003). Simulation of bi-direction pedestrian movement using a cellular automata model. *Physica A: Statistical Mechanics and Its Applications*, *321*(*3*), 633–640. https://doi.org/https://doi.org/10.1016/S0378-4371(02)01732-6

WHO. (2018). *Global status report on road safety 2018*. https://www.who.int/publications/i/item/9789241565684

Willis, A., Gjersoe, N., Havard, C., Kerridge, J., & Kukla, R. (2004). Human Movement Behaviour in Urban Spaces: Implications for the Design and Modelling of Effective Pedestrian Environments. *Environment and Planning B: Planning and Design*, *31*(*6*), 805–828. https://doi.org/10.1068/b3060

Xiao, Y., Xu, J., Chraibi, M., Zhang, J., & Gou, C. (2022). A generalized trajectories-based evaluation approach for pedestrian evacuation models. *Safety Science*, *147*, 105574. https://doi.org/https://doi.org/10.1016/j.ssci.2021.105574

Xu, S., & Duh, H. B.-L. (2010). A Simulation of Bonding Effects and Their Impacts on Pedestrian Dynamics. *IEEE Transactions on Intelligent Transportation Systems*, *11*(*1*), 153–161. https://doi.org/10.1109/TITS.2009.2036152

Yagil, D. (2000). Beliefs, motives and situational factors related to pedestrians' self-reported behavior at signal-controlled crossings. *Transportation Research Part F: Traffic Psychology and Behaviour*, *3*, 1–13. https://doi.org/10.1016/S1369-8478(00)00004-8

Yang, L., van Dam, K. H., Majumdar, A., Anvari, B., Ochieng, W. Y., & Zhang, L. (2019). Integrated design of transport infrastructure and public spaces considering human behavior: A review of state-of-the-art methods and tools. *Frontiers of Architectural Research*, *8*(*4*), 429–453. https://doi.org/https://doi.org/10.1016/j.foar.2019.08.003

Yannis, G., Papadimitriou, E., & Theofilatos, A. (2013). Pedestrian gap acceptance for mid-block street crossing. *Transportation Planning and Technology*, *36*(*5*), 450–462. https://doi.org/10.1080/03081060.2013.818274

Yucel, Z., Zanlungo, F., Feliciani, C., Gregorj, A., & Kanda, T. (2019). Identification of social relation within pedestrian dyads. *PLOS ONE*, *14*(*10*), e0223656. https://doi.org/10.1371/journal.pone.0223656

Yuen, J. K. K., & Lee, E. W. M. (2012). The effect of overtaking behavior on unidirectional pedestrian flow. *Safety Science*, *50*(*8*), 1704–1714. https://doi.org/https://doi.org/10.1016/j.ssci.2011.12.020

Zanlungo, F., Ikeda, T., & Kanda, T. (2014). Potential for the dynamics of pedestrians in a socially interacting group. *Physical Review E*, *89*(*1*), 12811. https://doi.org/10.1103/PhysRevE.89.012811

Zanlungo, F., Yücel, Z., & Kanda, T. (2019). Intrinsic group behaviour II: On the dependence of triad spatial dynamics on social and personal features; and on the effect of social interaction on small group dynamics. *PLOS ONE*, *14*(*12*), e0225704. https://doi.org/10.1371/journal.pone.0225704

Zhang, Y., & Fricker, J. D. (2021). Investigating temporal variations in pedestrian crossing behavior at semi-controlled crosswalks: A Bayesian multilevel modeling approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, *76*, 92–108. https://doi.org/https://doi.org/10.1016/j.trf.2020.11.002

Zivotofsky, A. Z., & Hausdorff, J. M. (2007). The sensory feedback mechanisms enabling couples to walk synchronously: An initial investigation. *Journal of NeuroEngineering and Rehabilitation*, *4*(*1*), 28. https://doi.org/10.1186/1743-0003-4-28

APPENDIX

Appendix A. Participants information

Table 66 – Appendix A. Participants information Site S1.

Site	Pedestrian	Cluster	Type of cluster	Sex	Age	Leg length
S1	P1	1	3M+2F	Male	26	0.97
S1	P2	1	3M+2F	Male	26	0.99
S1	P3	1	3M+2F	Female	24	0.97
S1	P4	1	3M+2F	Female	27	0.88
S1	P5	1	3M+2F	Male	28	1.17
S1	P6	2	3F+2M	Female	30	0.86
S1	P7	2	3F+2M	Female	25	0.96
S1	P8	2	3F+2M	Male	24	0.96
S1	P9	2	3F+2M	Female	36	0.95
S1	P10	2	3F+2M	Male	26	0.98
S1	P11	3	3M+2F	Male	40	1.20
S1	P12	3	3M+2F	Male	28	1.08
S1	P13	3	3M+2F	Male	24	0.96
S1	P14	3	3M+2F	Female	43	0.90
S1	P15	3	3M+2F	Female	24	0.97
S1	P16	4	3F+2M	Female	24	0.92
S1	P17	4	3F+2M	Female	30	0.95
S1	P18	4	3F+2M	Male	32	1.18
S1	P19	4	3F+2M	Male	27	0.97
S1	P20	4	3F+2M	Female	27	0.90
S1	P21	5	3M+2F	Male	30	0.89
S1	P22	5	3M+2F	Male	29	0.93
S1	P23	5	3M+2F	Female	25	0.87
S1	P24	5	3M+2F	Female	24	0.95
S1	P25	5	3M+2F	Male	26	0.97
S1	P26	6	3F+2M	Female	27	0.86
S1	P27	6	3F+2M	Female	27	0.99
S1	P28	6	3F+2M	Male	39	0.94
S1	P29	6	3F+2M	Male	27	0.99
S1	P30	6	3F+2M	Female	25	0.82

Table 67 – Appendix A. Participants information Site S2.

Site	Pedestrian	Cluster	Type of cluster	Sex	Age	Leg length
S2	P31	7	3F+2M	Male	28	1.08
S2	P32	7	3F+2M	Male	32	0.92
S2	P33	7	3F+2M	Female	31	0.87
S2	P34	7	3F+2M	Female	28	0.88
S2	P35	7	3F+2M	Female	27	0.83
S2	P36	8	3M+2F	Male	24	1.10
S2	P37	8	3M+2F	Male	24	0.97
S2	P38	8	3M+2F	Female	29	0.94
S2	P39	8	3M+2F	Female	24	0.96
S2	P40	8	3M+2F	Male	25	0.97
S2	P41	9	3M+2F	Male	29	1.00
S2	P42	9	3M+2F	Male	26	0.99
S2	P43	9	3M+2F	Female	28	0.91
S2	P44	9	3M+2F	Female	24	0.97
S2	P45	9	3M+2F	Male	25	0.95
S2	P46	10	3F+2M	Female	33	0.97
S2	P47	10	3F+2M	Female	27	0.85
S2	P48	10	3F+2M	Male	30	0.88
S2	P49	10	3F+2M	Male	26	0.98
S2	P50	10	3F+2M	Female	34	0.92
S2	P51	11	3M+2F	Male	25	0.98
S2	P52	11	3M+2F	Male	27	0.99
S2	P53	11	3M+2F	Female	27	0.92
S2	P54	11	3M+2F	Female	24	0.97
S2	P55	11	3M+2F	Male	25	0.98
S2	P56	12	3F+2M	Female	25	0.91
S2	P57	12	3F+2M	Female	24	0.97
S2	P58	12	3F+2M	Male	26	0.98
S2	P59	12	3F+2M	Male	33	0.98
S2	P60	12	3F+2M	Female	34	0.93

Table 68 – Appendix A. Participants information Site S3/Site PT.

Site	Pedestrian	Cluster	Type of cluster	Sex	Age	Leg length
S3	P61	13	3M+2F	Male	30	0.97
S3	P62	13	3M+2F	Male	30	0.97
S3	P63	13	3M+2F	Female	28	0.88
S3	P64	13	3M+2F	Female	24	0.97
S3	P65	13	3M+2F	Male	32	1.10
S3	P66	14	3F+2M	Female	33	0.90
S3	P67	14	3F+2M	Female	32	0.97
S3	P68	14	3F+2M	Male	25	0.96
S3	P69	14	3F+2M	Male	26	0.98
S3	P70	14	3F+2M	Female	28	0.89
S3	P71	15	3F+2M	Male	33	0.90
S3	P72	15	3F+2M	Female	32	0.97
S3	P73	15	3F+2M	Female	25	0.96
S3	P74	15	3F+2M	Male	26	0.98
S3	P75	15	3F+2M	Female	28	0.89
S3	P76	16	3M+2F	Male	23	1.01
S3	P77	16	3M+2F	Male	24	0.96
S3	P78	16	3M+2F	Female	23	0.93
S3	P79	16	3M+2F	Female	24	0.97
S3	P80	16	3M+2F	Male	23	0.94
S3	P81	17	3F+2M	Female	27	0.92
S3	P82	17	3F+2M	Male	24	1.10
S3	P83	17	3F+2M	Male	31	0.97
S3	P84	17	3F+2M	Female	27	0.96
S3	P85	17	3F+2M	Female	30	0.88
S3	P86	18	3M+2F	Male	32	0.95
S3	P87	18	3M+2F	Male	30	0.89
S3	P88	18	3M+2F	Female	24	0.97
S3	P89	18	3M+2F	Female	26	0.91
S3	P90	18	3M+2F	Male	27	0.99

Table 69 – Appendix A. Participants information Site CO.

Site	Pedestrian	Cluster	Type of cluster	Sex	Age	Leg length
CO	P1	1	3M+2F	Female	19	0.93
CO	P2	1	3M+2F	Female	19	0.93
CO	P3	1	3M+2F	Male	20	0.98
CO	P4	1	3M+2F	Male	19	0.96
CO	P5	1	3M+2F	Male	19	0.94
CO	P6	2	3F+2M	Female	20	0.82
CO	P7	2	3F+2M	Female	20	0.92
CO	P8	2	3F+2M	Female	18	0.95
CO	P9	2	3F+2M	Male	20	1.01
CO	P10	2	3F+2M	Male	23	0.99
CO	P11	3	3M+2F	Female	19	0.91
CO	P12	3	3M+2F	Female	24	0.87
CO	P13	3	3M+2F	Male	25	0.83
CO	P14	3	3M+2F	Male	44	0.94
CO	P15	3	3M+2F	Male	24	1.01
CO	P16	4	3F+2M	Male	24	0.86
CO	P17	4	3F+2M	Male	20	0.98
CO	P18	4	3F+2M	Female	19	0.82
CO	P19	4	3F+2M	Female	21	0.86
CO	P20	4	3F+2M	Female	25	0.87
CO	P21	5	3M+2F	Female	19	0.84
CO	P22	5	3M+2F	Female	20	0.86
CO	P23	5	3M+2F	Male	18	1.03
CO	P24	5	3M+2F	Male	25	0.89
CO	P25	5	3M+2F	Male	27	0.95
CO	P26	6	3F+2M	Male	28	0.94
CO	P27	6	3F+2M	Male	24	0.96
CO	P28	6	3F+2M	Female	40	0.85
CO	P29	6	3F+2M	Female	36	0.86
CO	P30	6	3F+2M	Female	22	0.96

Appendix B. Example of data collected.

The following Figures 81 and 82 present data collected from an experiment involving ID cluster 3, which correspond to cluster type 1 (three males and two females), conducted at Study Site S1. Each grid represents a single trajectory. Trajectories 1 to 12 depict movement from point A to point B, while trajectories 13 to 24 represent movement from point B to point A. The figures also provide information about the number of ID pedestrians and the sex composition of the group. "M" corresponds to male, and "F" corresponds to female.

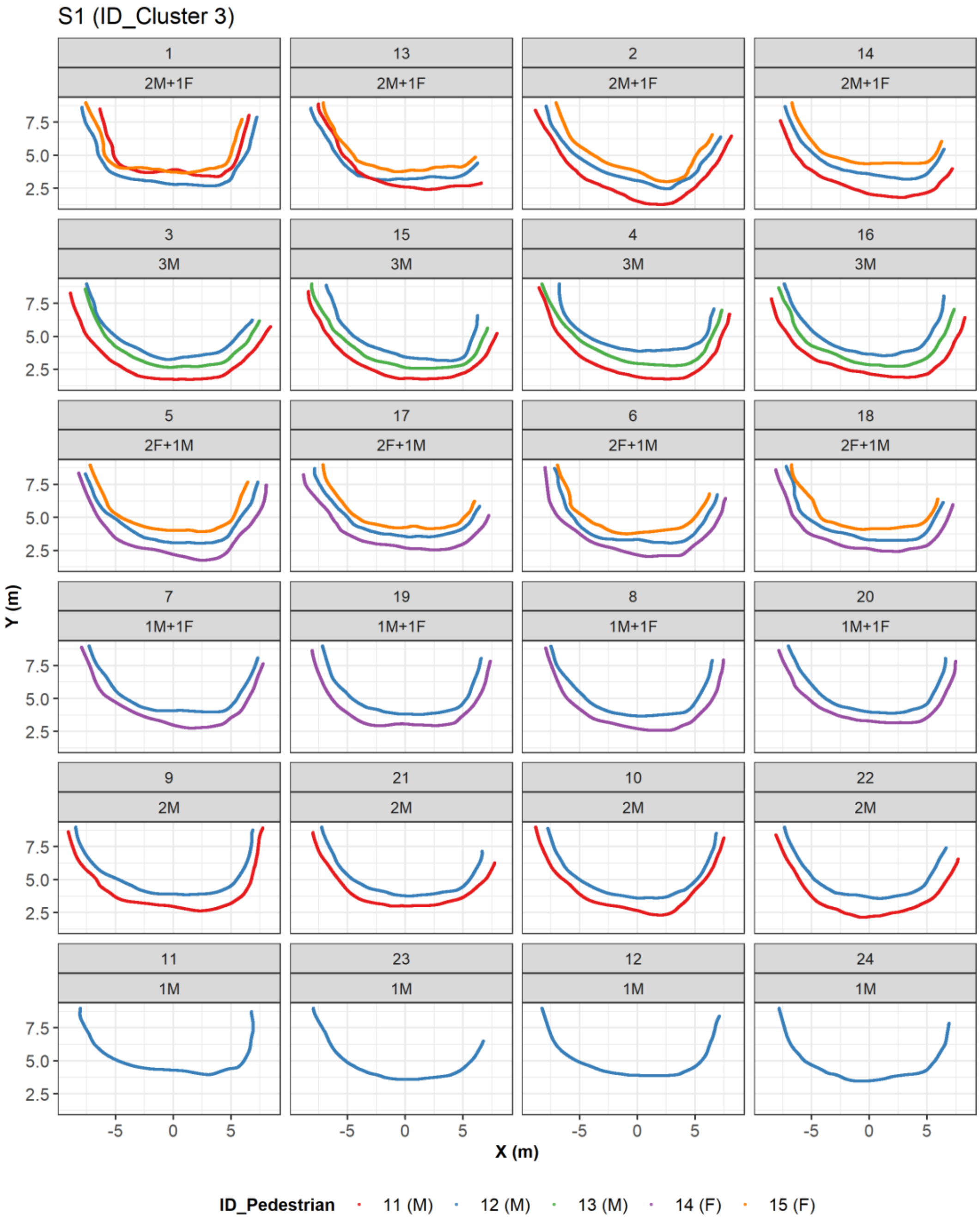


Figure 81. Appendix B: Example of trajectories data from ID_Cluster 3.

In addition, Figure 82 displays the walking speed of these pedestrians versus the relative duration of the trial. The vertical lines in this graph indicate the moments when each pedestrian first enters the crosswalk and then completes the crossing and arrives at the sidewalk on the other side of the street.

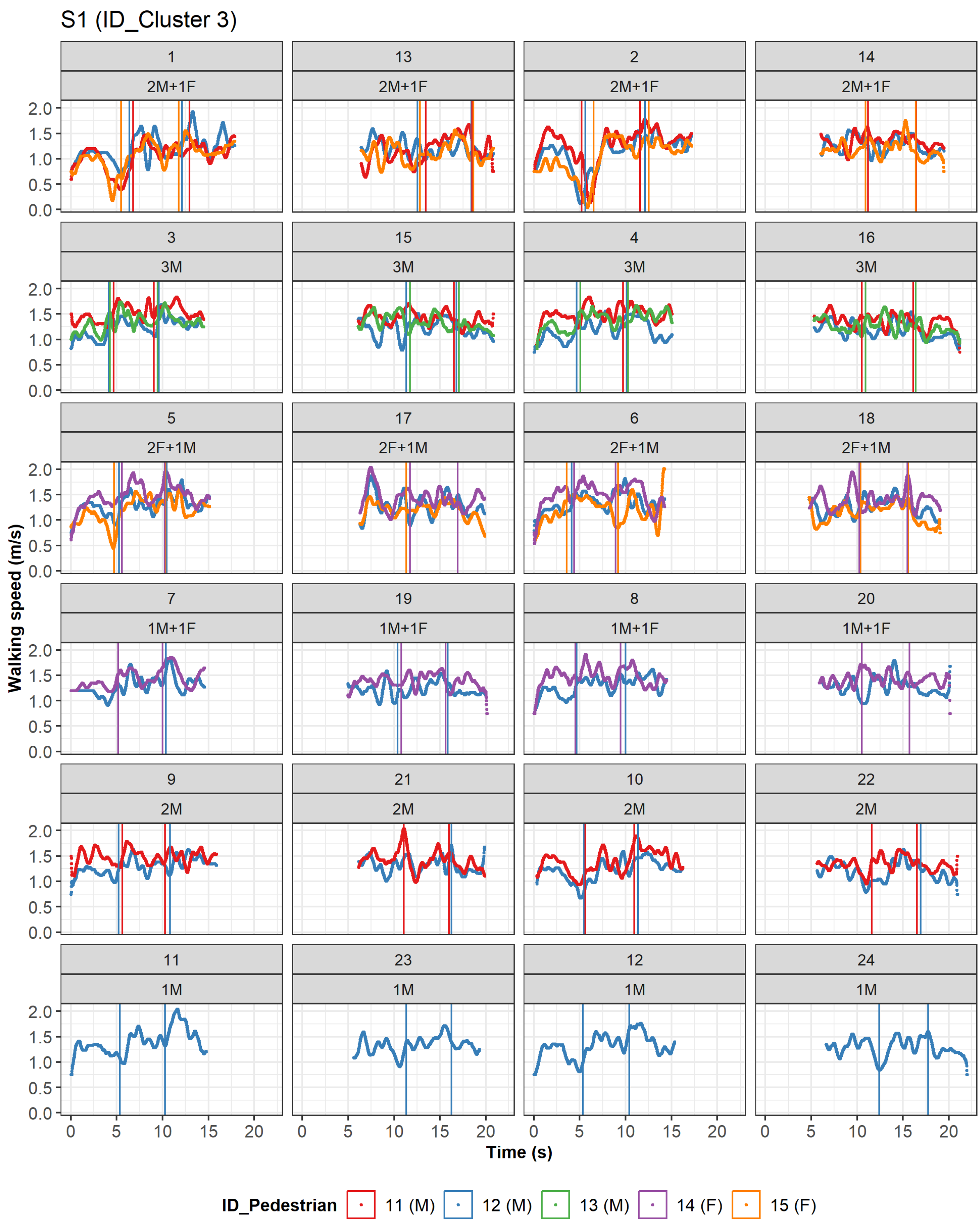


Figure 82. Appendix B: Example of walking speed data from ID_Cluster 3.

The Figures 83 and 84 present data collected from an experiment involving ID cluster 4, which correspond to cluster type 2 (three females and two males), conducted at Study Site S1.

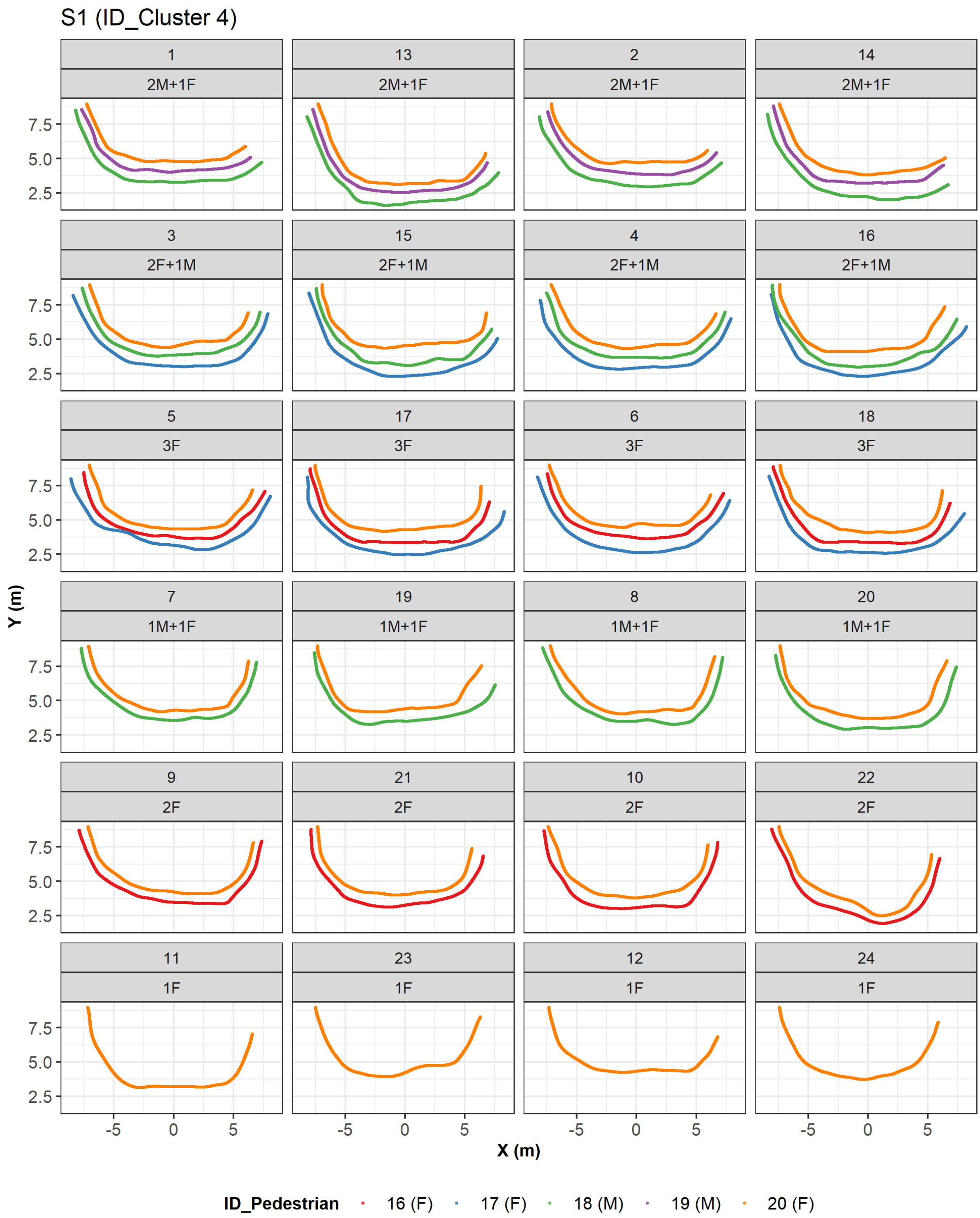


Figure 83. Appendix B: Example of trajectories data from ID_Cluster 4.

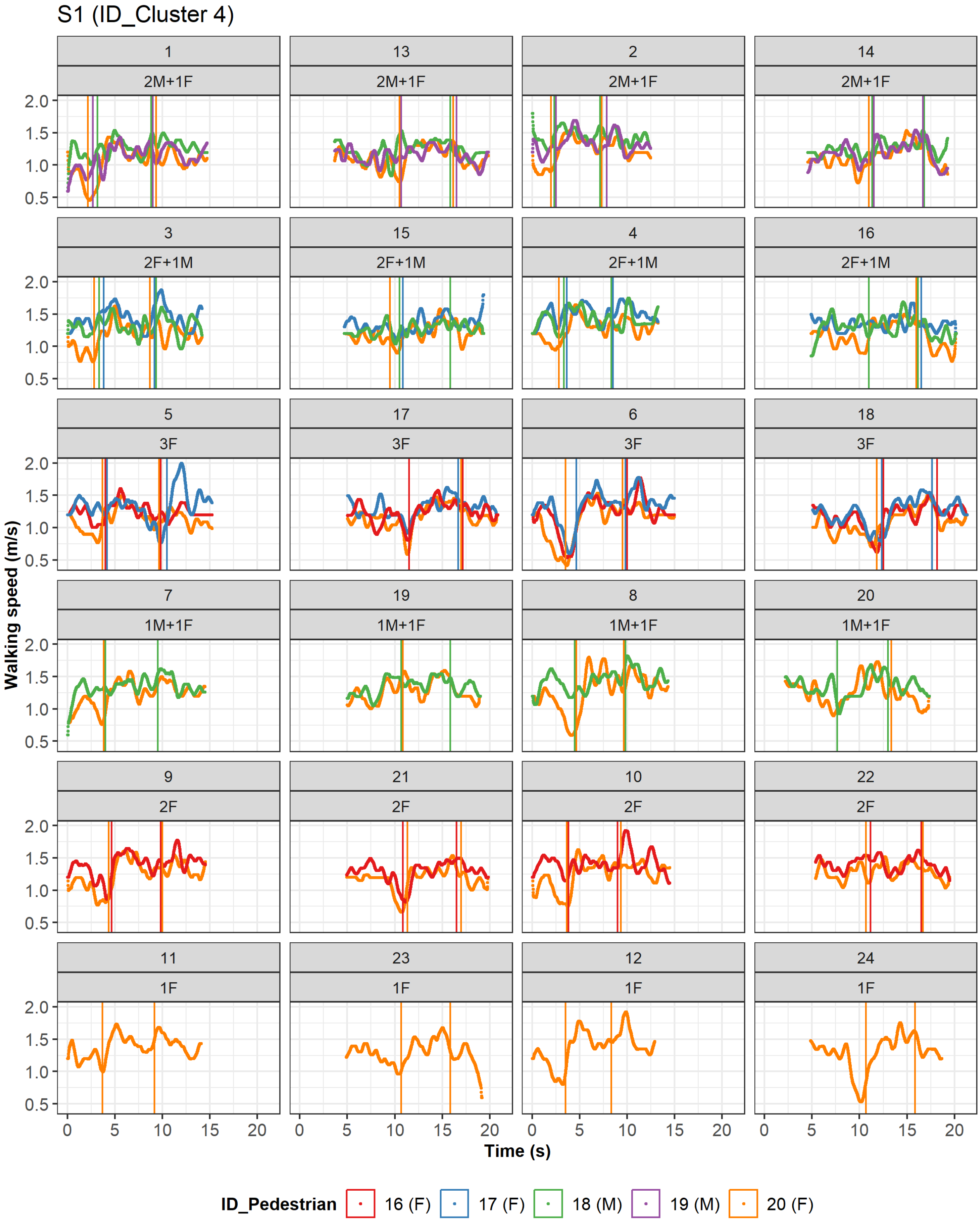


Figure 84. Appendix B: Example of walking speed data from ID_Cluster 4