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Will I cross when I see you crossing? Towards illegal pedestrian road crossing simulations

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► To cite this version:

Anjara Nobby Rakotoarivelo, Jean-Michel Auberlet, Roland Brémond. Will I cross when I see you crossing? Towards illegal pedestrian road crossing simulations. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2023, 93, pp.309-325. 10.1016/j.trf.2023.01.022 . hal-04434008

HAL Id: hal-04434008

<https://hal.science/hal-04434008v1>

Submitted on 7 Feb 2024

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TRF: Traffic Psychology and Behaviour

Will I cross when I see you crossing? Towards illegal pedestrian road crossing simulations

--Manuscript Draft--

Manuscript Number:	TRF-D-22-00365R3
Article Type:	Full Length Article
Keywords:	pedestrian modeling; street crossing decision; red light crossing; social influence; waiting time
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Manuscript Region of Origin:	Europe
Abstract:	<p>The temporal dimension (how long the pedestrian has been in a situation) and the social influence from the neighbor's behaviors are important factors in street crossing decisions. In this paper, we propose a preliminary agent-based model of the street crossing decisions at a pedestrian light without traffic based on three priors. First, a pedestrian agent is willing to wait a certain amount of time before crossing a street (we call it Accepted Waiting Time, AWT) and beyond that, it crosses even at a red light. The next two priors are based on Rosenbloom's work, who suggests that a pedestrian waiting at a red light may be influenced by those who are crossing or waiting. Combining these two priors leads to some kind of social influence, and we assume this social influence modulates the AWT of the pedestrian agent. Thus, in our simulations, agents supposed to cross at the red light may wait for the green light, influenced by waiting neighbors. Conversely, the window of opportunity of the neighbors crossing at the red light influences the waiting agents to cross as well. These results mean that the crossing decision would be different if the agents were alone. Moreover, agents with similar characteristics (in terms of AWT) and perceiving the same situation (color of the pedestrian traffic light and number of neighbors) but arriving at the crossing location at different times, will take different decisions (cross/ wait). Furthermore, the behaviors produced by our model are quite consistent with those reported in the literature, in terms of violation rate and waiting time. Further research are needed in order to include additional influence factors to this proof-of-concept model, and to take traffic into account.</p>
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Opposed Reviewers:	
Response to Reviewers:	

Contents lists available at [ScienceDirect](#)

Transportation Research Part F

journal homepage: www.elsevier.com/locate/dib

(anonymous submission)

Will I cross when I see you crossing? Towards illegal pedestrian road crossing simulations

ARTICLE INFO

Keywords:

pedestrian modeling
street crossing decision
red light crossing
social influence
waiting time

ABSTRACT

The temporal dimension (how long the pedestrian has been in a situation) and the social influence from the neighbor's behaviors are important factors in street crossing decisions. In this paper, we propose a preliminary agent-based model of the street crossing decisions at a pedestrian light without traffic based on three priors. First, a pedestrian agent is willing to wait a certain amount of time before crossing a street (we call it Accepted Waiting Time, AWT) and beyond that, it crosses even at a red light. The next two priors are based on Rosenbloom's work, who suggests that a pedestrian waiting at a red light may be influenced by those who are crossing or waiting. Combining these two priors **mimics** some **aspect** of social influence, and we assume this social influence modulates the AWT of the pedestrian agent. Thus, in our simulations, agents supposed to cross at the red light may wait for the green light, influenced by waiting neighbors. Conversely, the window of opportunity of the neighbors crossing at the red light influences the waiting agents to cross as well. These results mean that the crossing decision would be different if the agents were alone. Moreover, agents with similar characteristics (in terms of AWT) and perceiving the same situation (color of the pedestrian traffic light and number of neighbors) but arriving at the crossing location at different times, will take different decisions (cross/ wait). Furthermore, the behaviors produced by our model are quite consistent with those reported in the literature, in terms of violation rate and waiting time. Further research **is** needed in order to include additional influence factors to this proof-of-concept model, and to

<http://dx.doi.org/10.1016/j.dib.xxxx.xx.xxx>

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take traffic into account, which is needed before using the proposed model in virtual reality applications dedicated to children learning to cross roads.

1. Introduction

Street crossing at a signalized intersection is a complex task. Pedestrians want to cross and save time, but their actions are regulated by traffic rules and social rules. If the pedestrian traffic light is green, they are allowed to cross; otherwise, they should wait. However, not all pedestrians comply with the traffic rules and some of them are influenced by their neighbors to cross at a red light [Rosenbloom, 2009]: Police reports reveal that 39% of pedestrians cross during red lights [Diependaele, 2019]. The street crossing violation rates varies across locations. Rosenbloom [2009] found about 15% in Israel, while Diependaele [2019] found around 20 to 25% in major European cities and Yang et al. [2006] found up to 67% in Beijing. In terms of accidents, pedestrians are the most vulnerable road users [Mayeux et al., 2015], and most accidents involving pedestrians happen during street crossings [Lassarre et al., 2007, Zhuang et al., 2020]. About 17% of these accidents happen in the presence of fully functional traffic lights [Diependaele, 2019].

This paper proposes a street crossing decision model at the red light at without traffic, where simulated pedestrians base their decision on the perception of the contextual situation. The contextual information considered are the pedestrian traffic light color, actions (wait/ cross) of neighbors, and the time accepted by a simulated pedestrian to wait before crossing (Accepted Waiting Time, AWT, in the following). When the traffic color is red, the influence from neighbors modulates the AWT of the simulated pedestrians. This street crossing model is implemented in a multi-agent framework, in a scenario with pedestrian traffic lights without road traffic in a minor street. For a better understanding, two models are presented: in the Waiting Time model (WTM), the crossing decision only depends on the AWT, while the Social Influence Model (SIM) modulates the AWT (and thus the crossing decision) depending on the behaviors of neighbors. The proposed model is a first step towards virtual reality applications where children would learn to cross roads in more realistic environments in terms of the behavior of other pedestrians.

The organization of this paper is as follows: the literature review presents different studies in pedestrian behavior and in pedestrians simulations models (section 2). The street crossing decision models describe the characteristics of the pedestrians agents as a proof of concept (section 3). The models are then implemented and demonstrated with simulations (section 4) before a presentation of the main results (section 5) and a general discussion (section 6). The paper ends with a short conclusion, suggesting practical applications of the proposed model (section 7).

2. Literature review

This overview of the relevant literature is twofold. In section 2.1, we review current knowledge on pedestrian behavior, specifically at intersections. This review focuses on the social influence among pedestrians, as the proposed simulation model will use insight from this literature. In section 2.2, we propose an overview of current simulation models, with an emphasis on the gap between current knowledge and simulation models with respect to social influence.

2.1. Pedestrians behavior in street crossing

Different crossing violation rates have been observed in different sites and countries (see Tab. 1). Some of the differences between countries are attributed to differences in the regulation rules [Pelé et al., 2017]: In Hong Kong, for instance, violating the red light can lead to a fine if caught by a police [Zhu et al., 2022], while it is just a warning in some countries, such as Ireland [Rosenbloom, 2009]. Using videos to observe pedestrian behaviors has some limitations: the data is restricted to behavioral information, and motivational factors cannot be investigated. Using a questionnaire, Granié et al. [2013] found that about 21.1% of the pedestrians admit violating the traffic lights, including because they wanted to join their group. Self-reports, however, can lead to a social-desirability bias [Cantillo et al., 2015], where pedestrians tend to give a response that is viewed favorably. Dommes et al. [2015] combined observations and a questionnaire to study the red light crossing motivations. They found that violations were planned rather than opportunistic. **Such quantitative data may be useful for pedestrian model tuning, as it gives orders of magnitude of an emerging behavior which can be compared to what happens in the simulations.**

Methodology	Location	Violation rate	Reference
Observation	European cities	20-25%	[Diependaele, 2019]
Observation	Europe	39%	[Diependaele, 2019]
Observation	Israel	15%	[Rosenbloom, 2009]
Observation	Beijing (China)	23-67%	[Yang et al., 2006]
Observation	Beijing (peak hours)	39.9%	[Guo et al., 2011]
Observation	France	41.9%	[Pelé et al., 2017]
Observation	Japan	2.1%	[Pelé et al., 2017]
Questionnaire	France	28.8%	[Granié et al., 2013]
Both	Lille (France)	32%	[Dommes et al., 2015]

Table 1: Violation rates of pedestrians in various countries as reported by the literature.

2.1.1. Waiting time

Pedestrians wait a shorter time at unmarked compared to marked crossing. At unmarked crossings, Zhuang and Wu [2011] found that pedestrians wait a shorter time (around 3 s), never more than 25 s, and Zafri et al. [2019] found between 1 to 6 s. At a marked crosswalk, Das et al. [2005] found that 63.7% of the pedestrians wait for at least 20.8 s. The two situations indicate that pedestrians wait a shorter time when crossing at unmarked interactions where people tend to wait more actively, looking for new information, and wait for the next available gap to cross [Zhuang and Wu, 2011]. If a pedestrian fails to cross at his first attempt, they tend to wait longer before the second attempt [Shaaban et al., 2018]. Brosseau et al. [2013] observed several intersections in Sherbrooke (Canada), with only the red phase varying from one place to another. They found that a longer cycle duration leads to a higher violation rate. Also, people tend to wait less when the vehicle flow is low [Hamed, 2001].

Keegan and O'Mahony [2003] observed that after waiting for more than 20 s, pedestrians start making more unsafe crossings and violate the traffic rules. Younger pedestrians tend to wait shorter than older pedestrians [Nolan et al., 2008]. A group of pedestrians is found to wait longer than an individual [Hamed, 2001, Guo et al., 2011].

Regarding the pedestrian's waiting time recorded, it often lacks a description of the contextual situation during the crossing decisions. Using a camera to record the empirical waited time

based on the subtraction of the arriving time and crossing time is not enough to estimate how long the pedestrians would accept to wait at the kerb, that we call in the following the Accepted Waiting Time (AWT). These are two different concepts: the waited time is the time spent by a pedestrian on a sidewalk, while the AWT refers to the maximum time **they** accept to wait.

2.1.2. Social influence in crossing decisions

Humans are routinely exposed to each other's influence, for instance because they tend to comply with other people's behavior (normative influence) or because they tend to trust information from others (informational influence) [Asch, 1955, Deutsch and Gerard, 1955, Joule and Beauvois, 1987]. Road crossing is no exception: seeing someone crossing the street can influence a pedestrian's crossing decision. Das et al. [2005] found that even if pedestrians are not traveling together, they can be influenced by the crossing decision of others. When pedestrians arrive at an intersection with a pedestrian light, they are supposed to cross during green and wait during red. But not everyone follows the traffic rules, and when someone crosses, **they** encourage other pedestrians to follow [Rosenbloom, 2009].

Influence from neighbors may also work in the opposite direction, that is, encouraging people *not* to break the rules. Seeing someone waiting increases the compliance of pedestrians to follow the rules [Rosenbloom, 2009]. More people will comply with the traffic rules if they see someone who is already waiting [Lefkowitz et al., 1955].

2.2. Pedestrian models

Although walking is the oldest form of transportation, pedestrian behaviors receive less academic interest than vehicular traffic [Sheykhfard et al., 2021]. In some situations, pedestrian street crossing models are extended from road traffic models: for instance, Diaz [2002] developed a pedestrian street crossing model based on questionnaires designed for drivers. Some authors, focusing on optimizing the road traffic flow, consider pedestrians as a perturbation and delay to the traffic flow [Wang et al., 2021].

The simulation of street crossings require a decision model (cross or wait) as well as a navigation model (also described as "collision avoidance" model) for physically crossing the street; the Social Forces Model and the Optimal Reciprocal Collision Avoidance are among the most popular. Helbing and Molnar [1995] developed the Social Forces Model (SFM), which is composed of several forces (attraction to destination, repulsion to avoid collisions with other pedestrians and obstacles). Zanlungo et al. [2011] add the velocity of the neighbors to the input of the SFM model to predict future collision threats.

Van Den Berg et al. [2011] developed a velocity-based model for pedestrian simulation called Optimal Reciprocal Collision Avoidance (ORCA). The model uses the position, velocity and size of perceived neighbors to compute a new velocity. This new velocity is selected outside the "velocity obstacle" cone, formed with the perceived neighbors. A collision may happen if pedestrian agents do not select their velocity outside the cone. By using the velocity of the neighbors, ORCA agents can anticipate and correct their trajectory to avoid collisions. Computing the velocity is computationally expensive, but improves the performance during collision avoidance [van Toll and Pettré, 2021]. ORCA also allows pedestrians agents to react differently to another agent moving in the same or in the opposite direction, making the behaviors of simulated pedestrians more realistic. Therefore, the ORCA model will be used for the rest of this work.

2.2.1. Street crossing models

The simulation of street crossing may contribute to two types of studies. One addresses the pedestrian flow in an urban environment, in order to make *a priori* assessment of new facilities; these studies are usually conducted by human factors researchers and Departments of Transportation. The other type of studies focuses on improving our knowledge on pedestrian behaviors; these simulations use 3D environments in order to study the behaviors of participant in specific situations. In both cases, the simulation is cheaper, safer and faster to organize compared to on-site experiments.

Many empirical street crossing models have been proposed, combining various factors: environmental, and sometimes social (e.g. the behavior of neighbors). However, the results are difficult to generalize to different crossing locations or countries because they are empirically tuned to the data collected on one location. Our contribution focuses on the street crossing model. It is not empirical but grounded on several priors about the crossing behavior, from the applied psychology literature.

Dommes and Cavallo [2011], Zhuang et al. [2018] used logistic regressions to predict the crossing decision. Mayeux et al. [2015] developed a binary logit model, and use personal characteristics, spatial factors (position), and neighbors' decisions to compute the crossing decision. Faria et al. [2010] developed a street crossing simulation model using the distance between crossing neighbors as a factor in the crossing decision. In their model, a person is more likely to cross if their neighbors have started to cross. Their simulations of street crossing allow simulated pedestrians to influence each other to cross the street and break the traffic rules. However, in these simulations, the agents do not influence each other to wait and to comply with the traffic rules. Lefkowitz et al. [1955] and Rosenbloom [2009] observed that some pedestrians could see someone following the traffic rules and be influenced not to cross.

Relying uniquely on collected behavioral data has limitations. To collect these data, the experimenters isolate the variables under study, for example the impact of the waiting time. For instance, to study the impact of a countdown displays on pedestrians behaviors during red light crossings, Lipovac et al. [2013] only considered the behaviors of crossing pedestrians and the data was limited to the arriving time, waiting time, number of pedestrian crossings, and pedestrian characteristics (gender, age). They could not consider all contextual factors, such as the number of waiting pedestrians.

Yang et al. [2006] developed a street crossing model where simulated pedestrians can violate or comply with the traffic rules. At the beginning of a simulation, a proportion of compliant and opportunistic agents are generated. The opportunistic pedestrians agents cross when seeing someone crossing at a red light, and the compliant ones follow the traffic rules. This model has limitations: all agents waiting become opportunistic after seeing someone crossing. In actual situations, and depending on how long a pedestrian waits and on the behaviors of his neighbors, they might have different behavior. An opportunistic pedestrian might become compliant, or the reverse, depending on the context.

2.3. Objective of the paper

There is a discrepancy between the observed behavior of real pedestrians and the available pedestrian models and simulations, especially regarding the contextual situation during street crossing. More specifically, the accepted waiting time and the social influence from the decision of neighbors (crossing or waiting) are important factors in crossing decisions. This paper proposes two models of street crossing decision based on a temporal dimension (the accepted waiting time) and on social influence from crossing and waiting neighbors. It is demonstrated in

simulations at a traffic light without traffic, where we show that the model leads to qualitatively realistic behaviors, leading the path to more complex simulated pedestrians in the near future. **More specifically, the proposed models may be considered a first step towards more realistic models of the crossing decision which may contribute in the future to virtual reality applications helping children to learn how to cross a road safely.**

3. Agent-based model for street crossing

In this section, we describe our modelling of the crossing decision at a red light, taking into account the accepted waiting time and the social influence from other pedestrians at the same crossing. [Tolmie et al. \[2002\]](#) described street crossing as a series of four steps taken by a pedestrian. The first step consists of “identifying a safe crossing location” on the sidewalk. The second step is “awareness of the contextual situation”, meaning to be able to perceive the traffic light color and the behavior of others. The third step is identifying when to cross. The last step is “anticipation of the behaviors of vehicles”, assuming they will maintain a behavior for a certain period of time. Our models address the second and third steps, which are the awareness of the contextual situation and the identification of when to cross. Step 1 is not considered (the pedestrians all cross at the same place in our simplified model) and step 4 (interactions with the traffic) is left to future work. Thus, we focus on steps 2 and 3. Step 2 allows considering the environment (in our case, the color of the traffic light) and what people around are doing. Step 3 addresses time management, which includes finding a gap in the road traffic as well as choosing the right time to cross with respect to traffic lights. In the following, we propose two models: the Waiting Time Model (WTM) where the decision to cross is based on an individual parameter, the Accepted Waiting Time (AWT), and the Social Influence Model (SIM), which is identical to the WTM except that social influence dynamically modifies the accepted waiting time (MAWT).

The proposed models are presented in 3 steps. First, the architecture of the pedestrian agent is described in section 3.1. Then, its perception capacities are described in terms of perception of the physical information (section 3.2.1) and in terms of perception of the other pedestrians’ status with respect to crossing (section 3.2.2). The social influence model is described in section 3.3. It involves the notion of Accepted Waiting Time (AWT) introduced in section 3.4. Then, section 3.5 goes into the model implementation and section 3.6 emphasises the difference between the WTM and the SIM models.

3.1. Pedestrian agent

We use an agent approach to model the crossing decisions of pedestrians. The approach consists in a continuous cycle of perception-decision-action. Based on the perception of its neighborhood (traffic light, other agents), an agent takes a decision to cross or not at each time step, and the action module carries out a displacement, which modifies the neighborhood of the other agents.

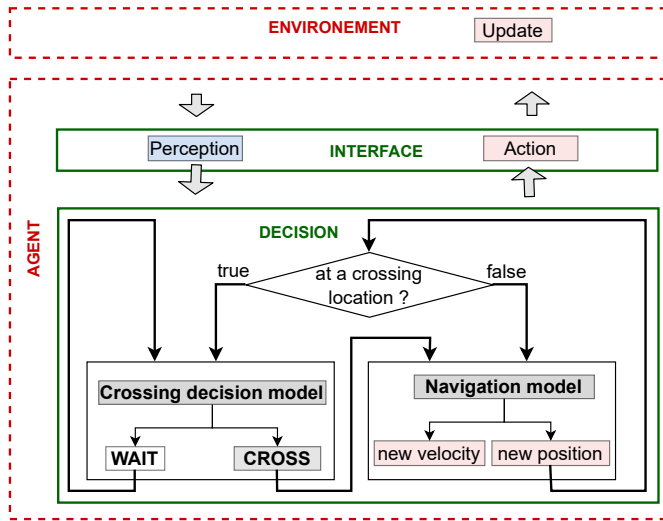


Fig. 1: Pedestrian agent architecture using the perception-decision-action framework. The environment is composed of a pedestrian traffic light, crossing location, neighbors, sidewalk, crosswalk, and street. The information perceived is used for the crossing decision model to cross or to wait, and for the navigation model to cross physically.

Figure 1 presents the architecture of a pedestrian agent (the same architecture for both models). An agent perceives information from the environment through the perception module. It takes decisions at two levels. The first one deals with the crossing decision, and the second one concerns the speed update. When the agent reaches the crossing point, it cognitively decides to cross or wait, and physically crosses using a navigation model when the decision is to cross. The navigation model is ORCA; it allows the pedestrian agent to reach his destination and to avoid collisions. In the proposed models, an agent cannot change his decision once it has decided to cross. At each time step, the environment updates the action of all agents.

3.2. Perception

The perception module distinguishes two types of information. The first one deals with physical data such as the speed and position of other agents, and color of the traffic lights. The second type of information concerns data interpreted by the agent. In the Social Influence Model (SIM), these data are related to what we call social information, that is, what other people do.

3.2.1. Physical information

A pedestrian can perceive the position and velocity of his neighbors, as well as the traffic light colors, within his perception range. According to the literature review, pedestrians perceive the majority of the information from urban environment through visual input. They can perceive up to 8 millions bit/s, but process only 7 bit/s [Feldstein and Dyszak, 2020]. In cases of attention overload, humans can ignore helpful information [Green and Senders, 2004]. According to Saaty and Ozdemir [2003], a human can only process information from 4 to 10 items simultaneously. On the other hand, pedestrians use a public distance around 8 meters [Hall et al., 1968], meaning that they do not consider what happens beyond this limit.

Therefore, we simulate pedestrians agents with a limited perception distance. This distance may depend on the local environment, for instance in street crossing where pedestrians need

to see across the street. Within this distance they can simultaneously perceive up to a limited number of neighbors. Their field of perception is 360 degrees: although the human visual field is around 120 degrees, auditory information is also relevant for street crossing and comes from all directions [de Lavalette et al., 2009].

Thus, in addition to the angular field of perception, the perception model uses two parameters: the perception distance and the maximum number of perceived neighbors.

3.2.2. Social information

As in real situations, where pedestrians can be influenced by their neighbors [Rosenbloom, 2009, Faria et al., 2010], we assume in the Social Influence Model that pedestrian agents simultaneously process physical and social information for crossing decisions. But social information has different meaning: Lefkowitz et al. [1955] considers that the social status of others is included in social information, while Giraldeau et al. [2002] describes the social information as the behaviors of other people. For simplicity, we follow Giraldeau et al. [2002] and limit social information to the actions of others.

To describe the actions of neighbors in a street crossing task, we classify their behavior. They have cognitive actions (“Wait” or “Cross”) and physical actions (“Stop” or “Walk”); furthermore, these actions depend on their location. For instance, “Walk” can be realized on the crossing location, on the sidewalk, or in the street. “Wait” and “Stop” can be realized only on the sidewalk at the crossing location (see Fig 2).

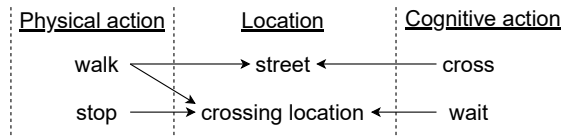


Fig. 2: Physical and cognitive actions of a pedestrian agent in a street crossing situation depending on its location.

The action of an agent can be described as a combination of physical and cognitive action. There are three possible combinations (see Table 2): “Walk/Wait”, “Walk/Cross”, and “Stop/Wait”. The first state “Walk/Wait” corresponds to an agent who arrives at the crossing location and walks to reach a position where it will wait. The second state “Walk/Cross” pertains to agents who are crossing the street. The last state “Stop/Wait” can occur after the first action “Walk/Wait” when the agent reaches his waiting location. In short, the agent arrives at the crossing location; if it cannot cross, it waits and possibly walks to a waiting position. During this short walk, it may decide to cross. When it stops, it waits until it decides to cross, and then walks again to cross. At each time step, all agents update their action state, and these states can be perceived by other agents. More actions states, such as running or stepping back, can be added in future work.

Table 2: State of the pedestrian agents before and during street crossing.

State	Description
walk/wait	An agent arrives at a crossing location and walks toward a spot to wait.
stop/wait	An agent arrives at the spot to wait and stop walking.
walk/cross	An agent crosses the street.

3.3. Social influence modeling

What we call social influence is the result of what the neighbors do. In the Social Influence Model (SIM), we assume that an agent may take a decision when alone, and that this decision may be different with other agents in his neighborhood. This is the reason why we propose two models, the Waiting Time Model (which will serve as a baseline) where the agents do not influence each other, and the Social Influence Model where they do, all other components of these models being the same.

According to [Rosenbloom \[2009\]](#) and [Faria et al. \[2010\]](#), at a crossing location during a red light, seeing neighbors illegally crossing influence pedestrians to cross. Indeed, the pedestrians who illegally cross show to those who are waiting that crossing is possible. Reciprocally, seeing neighbors waiting encourages a pedestrian to follow the traffic rules. In this last case, a pedestrian hesitates to break the traffic rules in the front of his neighbors, and prefers to wait longer. Thus, we have implemented the Social Influence Mode (SIM) with two priors based on previous work in applied psychology:

P_1 : crossing neighbors influence the agent to cross;

P_2 : waiting neighbors influence the agent to wait.

When an agent is in a “wait” state, we compute the social influence $\Delta^i(t)$ on agent i at time t as a linear combination of the number of waiting agents $N_W^i(t)$ and crossing agents $N_C^i(t)$ perceived by agent i . In order to weight differently the strength of each prior P_1 and P_2 , we introduce specific weight for N_W and N_C :

$$\Delta^i(t) = p_W \times N_W^i(t) - p_C \times N_C^i(t) \quad (1)$$

When agents are more rule-followers, p_W should be higher than p_C , when they are more rule-breakers p_C should be greater than p_W . Given that our goal is to propose a proof of concept, in the following simulations we have assumed that p_W and p_C are the same for all agents, but technically these values may be distributed among the simulated population.

Since the number of neighbors perceived simultaneously by a pedestrian agent is limited, the possible values of the social influence Δ can be computed prior to any simulation. We assume that a pedestrian can perceive up to 10 neighbors, which corresponds to the maximal number of items a human can process simultaneously [[Saaty and Ozdemir, 2003](#)]. This leads to 50 possible situations: Table 3 shows the values of Δ computed for two sets of parameters $\{p_W, p_C\}$.

Table 3: Social influence values for an agent perceiving up to ten neighbors. Green cells correspond to a positive influence to wait longer than when alone ($\Delta > 0$). Red cells correspond to a negative influence which may lead to a rule violation ($\Delta < 0$). In the blue cells, positive and negative influence are in equilibrium ($\Delta = 0$). White cells correspond to situations that an agent can not encounter, due to the limited number an agent can perceive

$N_C \backslash N_W$	0	1	2	3	4	5	6	7	8	9	10
0	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
1	-0.5	0	0.5	1	1.5	2	2.5	3	3.5	4	
2	-1	-0.5	0	0.5	1	1.5	2	2.5	3		
3	-1.5	-1	-0.5	0	0.5	1	1.5	2			
4	-2	-1.5	-1	-0.5	0	0.5	1				
5	-2.5	-2	-1.5	-1	-0.5	0					
6	-3	-2.5	-2	-1.5	-1						
7	-3.5	-3	-2.5	-2							
8	-4	-3.5	-3								
9	-4.5	-4									
10	-5										

(a) Social influence Δ with $\{p_W, p_C\} = \{0.5, 0.5\}$

$N_C \backslash N_W$	0	1	2	3	4	5	6	7	8	9	10
0	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
1	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1	0	
2	-1.8	-1.7	-1.6	-1.5	-1.4	-1.3	-1.2	-1.1	-1		
3	-2.7	-2.6	-2.5	-2.4	-2.3	-2.2	-2.1	-2			
4	-3.6	-3.5	-3.4	-3.3	-3.2	-3.1	-3				
5	-4.5	-4.4	-4.3	-4.2	-4.1	-4					
6	-5.4	-5.3	-5.2	-5.1	-5						
7	-6.3	-6.2	-6.1	-6							
8	-7.2	-7.1	-7								
9	-8.1	-8									
10	-9										

(b) Social influence Δ with $\{p_W, p_C\} = \{0.1, 0.9\}$

Tab. 3a is computed for $\{p_W, p_C\} = \{0.5, 0.5\}$: the influence of crossing and waiting agents have the same weights. If the numbers of perceived crossing and waiting agents are equal, $\Delta = 0$ (the agent is not influenced, blue cells in Tab. 3a). Social influence can be positive (green cells) when $N_W > N_C$ (the agent may wait longer than if they were alone), or negative (red cells) when $N_W < N_C$.

According to the literature review, the violation rate is often lower than the compliance rate with the traffic rules, meaning that N_W is probably often greater than N_C . Thus, we assume that $p_C > p_W$ in our simulations, which is illustrated Tab. 3b with $\{p_W, p_C\} = \{0.1, 0.9\}$. In this case, social influence is negative or null as soon as there is one crossing agent.

3.4. Accepted Waiting Time

As we said above, time perception may play a major role in crossing decisions, and we do not know the relationship between the observed waiting time before crossing and the maximum time that a pedestrian would accept to wait [Ullman et al., 2004]. Thus, we distinguish in our models the accepted waiting time (AWT) from the Waited Time (WT). The waited time is the amount of time a pedestrian spends at the crossing location before crossing; it can be observed in behavioral data and in simulations. The AWT is the red maximum time that a pedestrian accepts to wait before crossing; it cannot be directly estimated from behavioral data. Most available data focus on collecting the waited time. For example, Zhuang et al. [2018] measured the waited time using cameras.

We hypothesized that how long a pedestrian has been waiting on the crossing location impacts **their** crossing decision. According to Brosseau et al. [2013], people become impatient after 20 s, and may then take unsafe decision. Ullman et al. [2004] found that only 25% of pedestrians wait more 60 s. Thus, we introduce a third prior P_3 , assuming that pedestrians have limited accepted waiting time (AWT), and may violate the traffic rules if they wait longer than their individual AWT. This prior is grounded on psychological and observational evidence, and can be expressed as:

P_3 : an agent may cross if he waits more than his individual accepted waiting time.

It is implemented in both the Social Influence and in the Waiting Time models.

3.5. Relationship between social influence and accepted waiting time

Using the three priors P_1 , P_2 and P_3 , we assume that the accepted waiting time of an agent can be modified by the social influence computed by this agent, leading to a Modified Accepted Waiting Time (MAWT). In the SIM, the maximum time an agent may accept to wait evolves during the waiting phase and depends on the computed social influence. A negative value of Δ means that crossing agents have more influence than waiting agents, and according to P_1 , seeing crossing agents increases the willingness to cross. Thus, in terms of the Modified Accepted Waiting Time (MAWT), we assume that a negative value of Δ leads to temporarily decrease the MAWT. The same reasoning for positive values of Δ leads to consider that the MAWT increases when the influence of waiting agents is greater than the influence of crossing agents. Therefore, for each street crossing situation, the accepted waiting time of an agent may be temporarily different from his individual AWT.

3.5.1. Dynamics of the modified accepted waiting time

Arriving at a crossing location, a pedestrian agent perceives the traffic light. If it is red, a waiting phase begins. His waited time starts from 0 and increases at each time step, while his accepted waiting time evolves depending on the computed social influence $\Delta^i(t)$. Thus, in the Social Influence model, we define a Modified Accepted Waiting Time $MAWT^i(t)$ which is the current accepted waiting time of agent i at time t . $MAWT$ is initialized to the individual AWT ($MAWT^i(0) = AWT^i$) when the agent arrives at a crossing location. Then, it is modified at each time step by a factor $\psi^i(t)$ which depends on the computed social influence $\Delta^i(t)$. $\psi^i(t)$ is given by:

$$\psi^i(t) = \left[1 + \frac{\Delta^i(t)}{100} \right] \quad (2)$$

Then the updated $MAWT^i(t)$ is given by:

$$MAWT^i(t) = MAWT^i(t - TS) \times \psi^i(t) \quad (3)$$

where TS is the time step of the simulation. $MAWT^i$ may decrease or increase depending on what the neighbors do. In this preliminary model, ψ is bounded in range, so that the speed of variation of $MAWT$ is limited: the AWT of an agent cannot change too fast.

To evaluate the impact of social influence in our Social Influence Model (SIM), we have designed a second model called the Waiting Time Model (WTM). In this model, the accepted

waiting time does not depend on what the neighbors do. The Waiting Time Model is the same as the Social Influence Model except that $\Delta = 0$ all the time for all agents, leading to $\psi = 1$, and $MAWT(t) = AWT$.

3.5.2. Maximum value of the MAWT

Over a period of time with $\psi > 1$, MAWT may reach very high values. For instance, MAWT may become greater than 60 seconds, which is a typical duration of a pedestrian traffic light [NACTO]. Considering an agent continuously perceiving 8 waiting and 2 crossing neighbors with $p_C = p_W = 0.5$, we compute $\psi^i(t) = 1.04$. If $AWT=30$ s and with a simulation time step $TS=0.1$ s, $MAWT^i(t)$ exceeds 60 s after 3 seconds of waiting. This is why the value of MAWT is limited by an individual threshold T^i in our model: $T^i = AWT^i \times PT$, where PT is a dimensionless percentage parameter, for instance 120%, that is applied to all agents in the simulation. PT prevents MAWT to be higher than an individual threshold T^i .

3.6. Crossing decision

When an agent reaches its modified accepted waiting time, he decides to cross, even at a red light. Fig. 3 illustrates the crossing decision with the two proposed models.

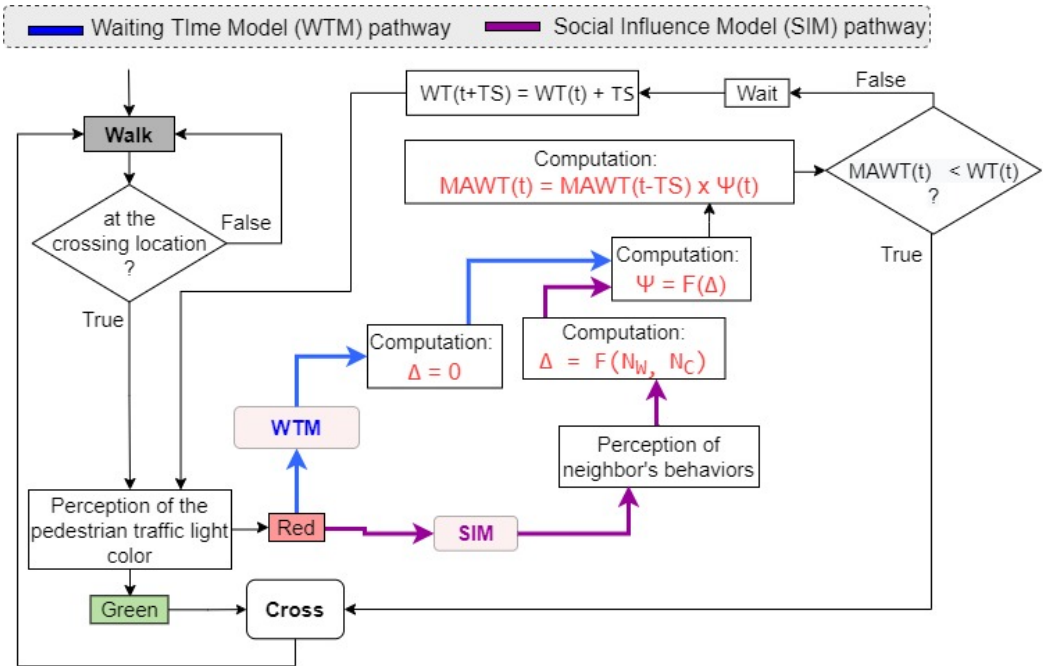


Fig. 3: Crossing decision processes in the SIM and WTM models. The two models share most of the algorithm, the difference (computation of Δ) is highlighted in blue (WTM) and purple (SIM).

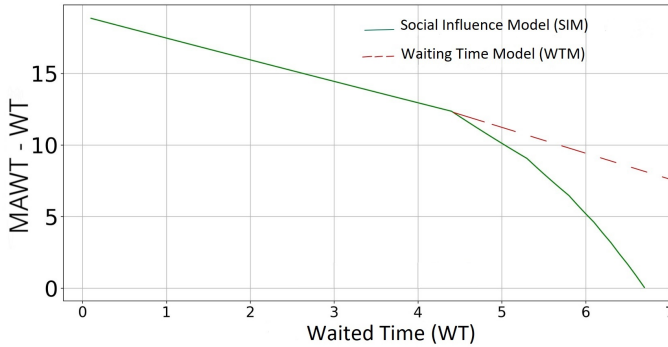


Fig. 4: Example of the time course of the Modified Accepted Waiting Time (MAWT) in the Social Influence Model (continuous line) and in the Waiting Time Model. The agent crosses the street when $MAWT(t) - WT(t) < 0$.

Fig. 4 illustrates the evolution of waited time of a pedestrian agent. In one case (SIM), the agent is influenced by several neighbors, in the other case (WTM) he decides as if he were alone. The waited time is on the x-axis, and the difference $MAWT - WT$ is on the y-axis. Once $MAWT - WT > 0$, the agent crosses the street. In this example, $MAWT(t) - WT$ decreases linearly in the first 4 s for the two models, because there is no social influence, which may corresponds to two situations: the agent may be alone, or the influence of crossing and waiting agents may counterbalance each other. After about 4.3 seconds, $MAWT - WT$ decreases more quickly for the SIM. It means that more agents are crossing, and after 6.8 s the agent crosses the street with the SIM, or still waits with the WTM.

4. Simulations

This section describes the method used to simulate street crossing scenarios in a minor street without road traffic, with the aim of demonstrating the potential benefit of the proposed Social Influence Model.

Pedestrian agents follow a predefined itinerary. When they reach a crossing location, defined as a waiting zone on the sidewalk, they collect information from the traffic light and from their neighbors in their perception range. If the light is green, they cross. Otherwise, they begin to wait and move inside the waiting zone to a waiting spot. Once they have decided to cross, they physically cross the street without updating their decision. The traffic light may be red or green, with a different duration for each color. A crossing is labeled illegal if the agent starts crossing at a red light; otherwise, it is labeled legal crossing. A legal crossing may happen when someone arrives during the green phase or when someone arrives during the red phase and waits until the traffic light turns to green.

4.1. Environment

The street width is 7.19 m, corresponding to a two-way street. The pedestrian agents follow a closed loop itinerary of 67.64 m (see Fig. 5). The closed loop allows keeping the number of simulated pedestrians constant during a simulation. At a red light, the agents move inside the waiting zone to find a spot to wait. If an agent decides to cross before reaching this spot, it may cross directly. After crossing the street, it make a new lap on the same itinerary. A waiting zone is designed: it is an informal area where pedestrian agents are allowed to consider crossing the

street. It is an $2.4 \text{ m} \times 6.72 \text{ m}$ rectangular area inside the sidewalk (Fig. 5). It contains two rows of 10 positions, each position can contain up to two agents, leading to a maximal capacity of 40 agents waiting simultaneously.

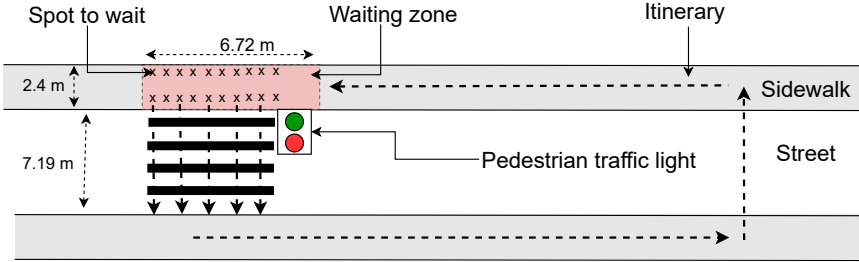


Fig. 5: Environment for the street crossing simulation.

4.2. Initial conditions

An agent is perceived by other agents as a 2D disc; they all have the same diameter size of 0.4 m. They all have the same perception characteristics: they can see up to 10 neighbors all around them. The perception range is 10 m, which is enough for an agent to perceive all waiting and crossing neighbors; it is also close to the public distance according to Hall et al. [1968].

Two populations of pedestrians agents have been generated, called H and M . The H population is faster and more homogeneous than the M population in terms of desired speeds. For each population, we used two levels of agents density. The low density corresponds to 10 agents (one every 6.70 m on the itinerary), while the higher density corresponds to 40 agents (one every 1.68 m).

The agents' desired speed are chosen from normal distributions. The mean speed of the H population is $v_H = 1.16 \text{ m/s}$, with a low standard deviation $\sigma_H = 0.05 \text{ m/s}$. It corresponds to the average speed of older pedestrians in a study by Fitzpatrick et al. [2006]. The desired speed range is controlled with a minimal and a maximal speed value, set to $v_{min} = V_{mean} - 3\sigma$ and $v_{max} = V_{mean} + 3\sigma$. The parameters of the H population are:

$$H : \begin{cases} v \in \mathcal{N}(\mu = 1.16 \text{ m/s}, \sigma = 0.05 \text{ m/s}) \\ v_{min} = 1.01 \text{ m/s} \\ v_{max} = 1.31 \text{ m/s} \end{cases} \quad (4)$$

The M population has a mean desired speed of 1.3 m/s, and a large standard deviation ($\sigma_M = 0.3$). This mean speed is the average of the mean speeds of older and younger pedestrians in Fitzpatrick et al. [2006] (resp. 1.16 and 1.45 m/s). The parameters of the M population are:

$$M : \begin{cases} v \in \mathcal{N}(\mu = 1.30 \text{ m/s}, \sigma = 0.30 \text{ m/s}) \\ v_{min} = 0.80 \text{ m/s} \\ v_{max} = 2.20 \text{ m/s} \end{cases} \quad (5)$$

The individual accepted waiting time (AWT) is also chosen in a normal distribution. According to Ullman et al. [2004], pedestrians become less patient after 20 s of waiting, and only 25% wait more than 60 s. [Ishaque and Noland, 2008] found that pedestrian's impatience can be

noticed after 15 s. Thus, we used a mean value of 40 s and a standard deviation of 8 s, with a minimum value of 20 s and the 75th percentile set to 60 s, leading to:

$$(H \text{ and } M) : \begin{cases} AWT \in \mathcal{N}(\mu = 40 \text{ s}, \sigma = 8 \text{ s}) \\ AWT_{min} = 20 \text{ s} \\ AWT_{max} = 64 \text{ s} \end{cases} \quad (6)$$

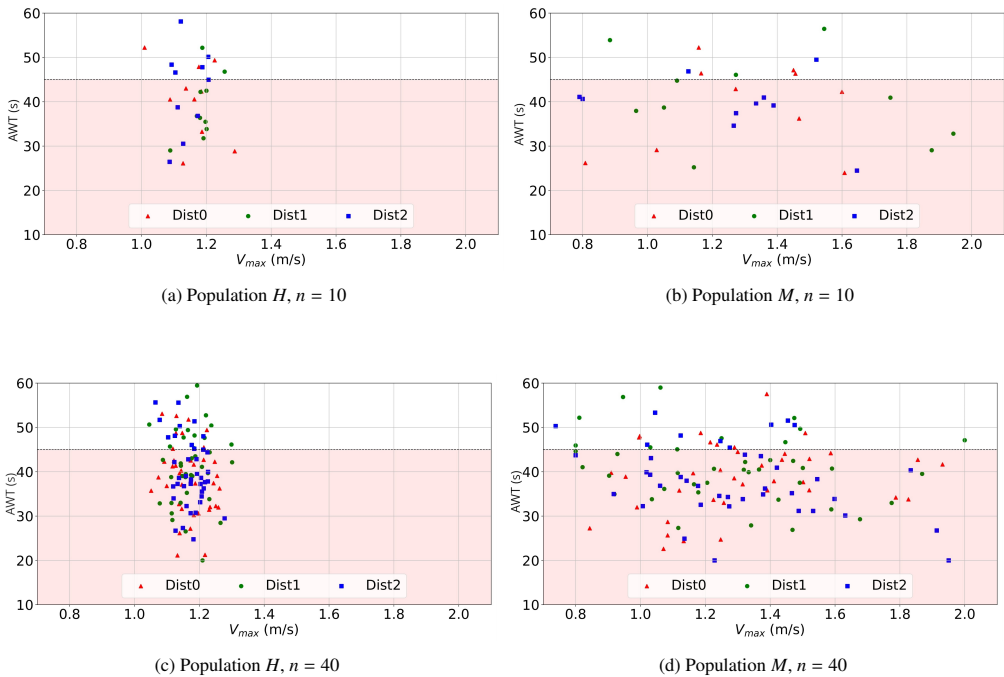


Fig. 6: Individual accepted waiting times and desired speed for each of the four simulated populations. The colored zone in each figure represents the red light phase. Three distribution have been simulated for each type of population: *Dist0*, *Dist1* and *Dist2* correspond to the three samplings of each pedestrian population.

Fig. 6 describe the four simulated populations, with three sampling (*Dist0*, *Dist1* & *Dist2*) for each population. The lower zone (colored) in each figure represents the red light phase. The number of agents with $AWT > 45s$ is 19 (resp. 49) for $n = 10$ (resp. $n = 40$), which leads to violation rates of 31.67% (resp. 20.41%). These percentages correspond to the violation rates if the agents arrive at the beginning of the red phase and if social influence does not modify their accepted waiting time.

As seen above, the Modified AWT (MAWT) is limited with a threshold. In the simulations, this threshold is set either to 110% or 120% of the agent's individual accepted waiting time. The possible increase of MAWT ranges between 2 to 6 s.

At the beginning of each simulation, the agents are randomly positioned along the itinerary, outside the waiting zone and the crosswalk. Each simulation lasts 600 simulated seconds, corresponding to 10 traffic light cycle : the traffic light cycle is 60 s with 45 s of red and 15 s of green. This cycle is consistent with the MUTCD's recommendation for minor streets [NACTO].

All simulations start with a red light, and the time step is $TS = 0.1$ s. Each simulation is repeated 3 times (with 3 samplings for each type of population, see Fig. 6), leading to 3 samplings \times 2 populations (H and M) \times 2 agent densities (low and high) \times 2 thresholds (110 and 120%) \times 2 sets of parameters p_C and p_W , with a total of 48 simulations. 12 more simulations correspond to the WTM (3 samplings \times 2 populations \times 2 agent densities). Depending on the simulation parameters and on the agent's situations, an agent can cross the street between 6 and 10 times during the 600 simulated second. We expected that in each population, many different situations would occur, helping to assess the relevance of the proposed crossing decision model.

4.3. Implementation of the Social Influence Model (SIM)

The core of the Social Influence Model was implemented with algorithm 1. An artifact was needed, because as soon as $MAWT$ reaches AWT , we observed that $MAWT - WT < 0$, that is, the agent crosses the street. Thus, no increase of $MAWT$ above AWT could be observed, that is, no agent waiting longer than expected (see prior P_2). In order to observe this kind of behavior, the crossing decision algorithm was modified. The decision is to cross if:

$$\begin{cases} WT^i(t) > PT \times AWT^i \\ or \\ WT^i(t) > MAWT^i(t) \text{ and } MAWT^i(t) < AWT^i \end{cases} \quad (7)$$

Algorithm 1: Social Influence Model

```

/* INITIALIZATION SIMULATION */
1 GlobalTime ← 0; // Init simulation time
/* END INITIALIZATION SIMULATION */
/* INITIALIZATION WAITING */
2 WTi(t) ← 0; // when a pedestrian agent start to wait
3 MAWTi(t) ← AWTi Ti ← AWTi × PT; // PT(%):threshold parameter
/* END INITIALIZATION WAITING */
4 if (isAtCrossingLocation=True) AND (isRedLight=True) then
5   Δi(t) = pw × Nwi(t) - pc × Nci(t)
6   ψi(t) = [1 + Δi(t)/100]
7   MAWTi(t) ← MAWTi(t) × ψi(t);
8   if MAWTi(t) > Ti then
9     MAWTi(t) ← Ti
10  if [WTi(t) > Ti] then
11    cross()
12    /* After starting to cross, MAWT and WT are re-initialized */
13    MAWTi(t) ← AWTi
14    WTi(t) ← 0
15  else
16    if [(MAWTi(t) < AWTi) AND (MAWTi(t) < WTi(t))] then
17      cross(); // The waiting time reaches the MAWTi, then cross.
18      MAWTi(t) ← AWTi
19      WTi(t) ← 0
20    else
21      WTi(t + 1) ← WTi(t) + TS; // Wait
22 GlobalTime ← GlobalTime + TS

```

With this modified algorithm, $MAWT^i(t)$ can reach its maximal value $T^i = PT \times AWT^i$, because when $WT^i(t)$ is between AWT^i and this threshold, the agent does not decide to cross.

The simulations have been conducted on a DELL laptop with a GPU Intel UHD Graphics 630 NVIDIA GeForce GTX 1060, 8 Giga of memory. Core i7 was used for the simulations, together with the Unity 3D engine and the ORCA model version C# [Van Den Berg et al., 2010].

5. Results

This section presents the results of the street crossing simulations. Its main purpose is to emphasize the potential of the Social Influence model (SIM) to create non-normative pedestrian behaviors, leading to more realistic collective behaviors compared to the state of the art. The Waiting Time model (WTM) is used as a baseline. We first analyze the violation rates, showing the consistency of the simulated crossing behaviors at the red light with respect to observed behaviors. Then, the model is investigated in more details, and different types of street crossing are observed through the analysis of XT diagrams. Finally, we discuss the role of the accepted waiting time (AWT).

5.1. Violation rates

Table 4 presents the crossing violation rates for all simulations. “Expected” or V_0 is the expected decision based on the difference between the individual AWT and the remaining red light duration when a pedestrian arrived in the waiting zone. “Observed” refers to the decision realized by pedestrians when they cross. V_1 represents the violation percentage of all pedestrian crossings. V_2 is the violation rate for pedestrians arriving at a red light. WTM is the Waiting Time model (without social influence), SIM_1 (resp. SIM_2) is the Social Influence Model with $p_W = p_C = 0.5$ (resp. $p_W = 0.9$ and $p_C = 0.1$).

Table 4: Violation rates for all simulations. H and M refer to the homogeneous and mixed population. n refers to the number of simulated pedestrians. PT is the MAWT threshold percentage.

Pop	Models		PT (%)	Expected		Observed			
				Red phase only V_0 (%)		Overall V_1 (%)		Red phase only V_2 (%)	
				n=10	n=40	n=10	n=40	n=10	n=40
H	WTM			23.96	34.33	9.50	18.46	23.96	34.33
	SIM	SIM_1	110	31.27	33.53	9.03	11.98	24.57	22
			120	33.16	33.87	7.46	6.91	20.53	13.45
		SIM_2	110	28.16	31.75	12.23	14.08	32.65	26.31
			120	29.17	34.39	10.83	10.08	27.08	20.25
M	WTM			6.91	14.52	5.28	9.67	6.91	14.52
	SIM	SIM_1	110	8.77	14.73	5.09	6.74	6.71	10.03
			120	8.25	15.10	3.12	4.90	4.12	7.44
		SIM_2	110	8.70	15.09	5.09	8.45	6.65	12.52
			120	7.23	15.35	2.74	9.92	3.61	14.23

The comparison of V_0 and V_2 indicates lower values for V_2 with the SIM (not with the WTM), meaning the accepted waiting time is dynamically modified, pedestrians agents are more influenced by waiting than by crossing agents. They tend to wait longer than what would have happened if they were alone or without social influence.

According to the literature review, the percentage of rule-breakers is lower than rule-followers in real life. For example, the violation rates in major European cities are around 20 to 25% [Diependaele, 2019]. The violation rate V_1 is higher with $n = 40$ (10.12% in average) than with $n = 10$ (7.04%). There are more groups of pedestrian crossing together with 40 pedestrians, which presumably influenced more waiting pedestrians to cross. For population H , most values of V_2 are above 20%. The SIM model allows some pedestrian agents to cross at the red light with a violation rate in the range of what is found in the literature.

5.2. Impact of social influence on the crossing decisions

To analyze the impact of social influence on crossing decisions, we have compared the expected and observed crossing decision with the SIM, for pedestrians crossing at red lights. The expected decisions are computed when the pedestrians enter the waiting zone. The color of the light for the expected and actual crossing decisions are collected during the simulations (actual is when the pedestrian starts crossing). This leads to four possible situations, denoted RR , GR , GG , and RG (R for Red, G for Green, see Table 5). RR means that the agent is expected to cross at red, and crossed at the red light; GR means that the agent is expected to wait for the green and

crossed at the red; *GG* means that the agent is expected to wait for the green and indeed crossed at the green; *RG* means that the agent is expected to cross at red and finally crossed at the green.

Table 5: Proportion of each crossing class: *RR*, *GR*, *GG*, and *RG* in all simulations.

Model	RR(%)		GR(%)		GG(%)		RG(%)	
	10	40	10	40	10	40	10	40
<i>WTM</i>	15.44	24.43	0	0	84.46	75.58	0	0
<i>SIM</i>	12.14	13.84	3.61	1.94	77.06	73.84	7.20	10.39

The impact of social influence appears Table 5, comparing the Social Influence and Waiting Time models: some pedestrians are influenced by what their neighbors decide (*GR* and *RG* columns), which cannot happen with the Waiting Time model. Note that when a pedestrian has the same expected and observed crossings, it does not mean he was not influenced, only that the influence was not strong enough to change his decision.

5.3. X/Time diagrams of crossing pedestrians

X/Time diagrams show the positions of all mobiles in a spatial area and their evolution with time. Fig. 7 shows examples of X/Time representations of pedestrians crossing the street from the waiting zone (bottom of the figure) to the other side of the street (top of the figure). The total time displayed is one 60 s cycle of the pedestrian light (45 s red and 15 s green; the color is used as a background in the figure). Pedestrians starting their crossing at a green light have their trajectory colored in green (legal crossing), the other ones are in red (illegal crossing).

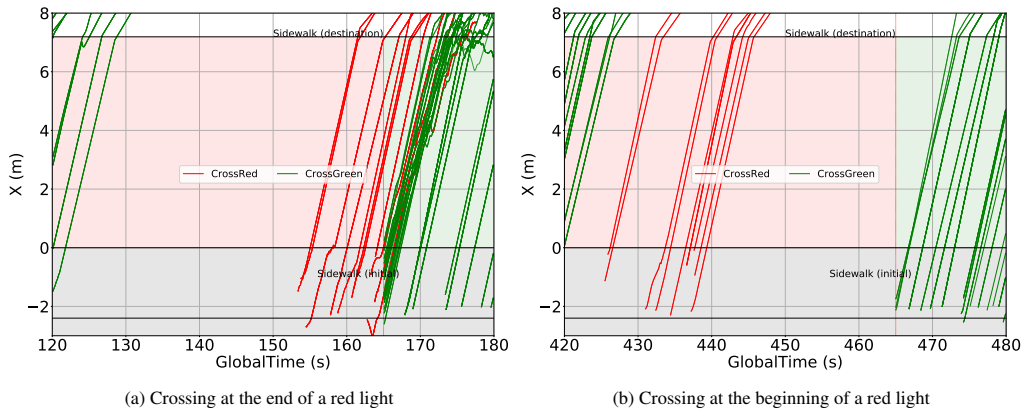


Fig. 7: X/Time diagrams of crossing pedestrian agents using the Social Influence Model. The vertical axis represents the spatial position of the agents across the street, and the horizontal axis is the simulation time. The background represents the color of the traffic light. The origin of the vertical axis is set to the roadside near the waiting zone. The trajectories start in the waiting zone, when an agent decides to cross, and each plot represents a trajectory. The green ones are legal crossings and the red ones illegal crossings.

Figure 7a shows several pedestrians waiting together while the pedestrian light is red. Then, some of them decide to violate the traffic rules, while others wait for the green light. It is interesting to see different pedestrians taking different decisions (wait/cross) based on their perception of the same situation. Figure 7b shows several pedestrians crossing together at the end of a green light. Some of them have not finished their crossing when the light turns red (top left of the

figure). A few seconds later, more pedestrians arrive at the beginning of the red light and see these pedestrians crossing at the red light. They are influenced to violate the traffic rules, leading them to cross at the beginning of the red light.

The trajectories of pedestrians displayed in the X/Time diagrams are consistent with the model’s priors, and can be compared to observations from Lipovac et al. [2013] who found, at a street crossing without countdown, more violations at the beginning (during the first 4 s) and at the end of the red light (for waiting times higher than 34 s). In our simulations, seeing several pedestrian crossing influences those arriving at the sidewalk, and increases the violation rate in the simulations. However, Ishaque and Noland [2008] suggested that pedestrians do not necessary become impatient after waiting a long time, they may become more compliant because they know the pedestrian light will soon turn to green.

5.4. Accepted Waiting Time

Figure 8 compares the modified accepted waiting time *MAWT* with the accepted waiting time *AWT* for pedestrians crossing at red lights, in all simulations. If a pedestrian is not influenced, the two values are the same, plotted on the diagonal. A crossing below the diagonal indicates the pedestrian was influenced to cross, while above the diagonal he was influenced to wait.

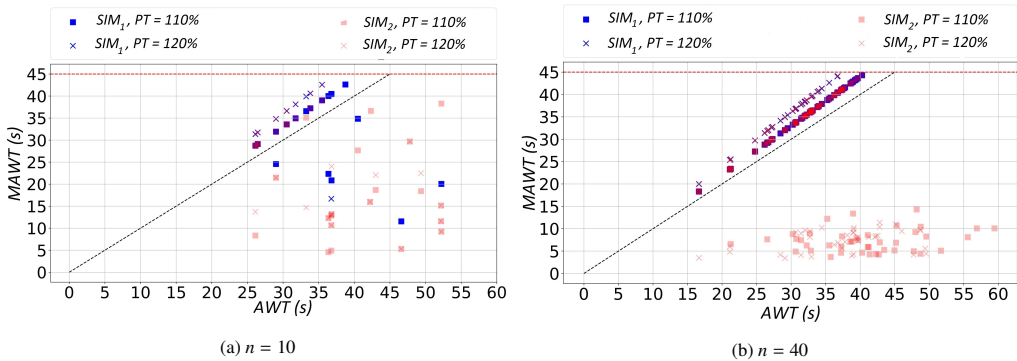


Fig. 8: Plots of the modified accepted waiting time (*MAWT*, vertical axis) at the moment of crossing at a red light, versus the *AWT* (horizontal axis), for all simulations with the *SIM*. *SI*₁ (plain squares) correspond to $p_C = p_W = 0.5$, while *SI*₂ (crosses) correspond to $p_C = 0.9$ and $p_W = 0.1$. Square plots (resp. crosses) are for simulations with $PT=110\%$ (resp. 120%). The horizontal red line is the duration of the red light. Left: simulations with 10 pedestrians; Right: 40 pedestrians.

Figure 9 illustrates the evolution of *MAWT* with the *SIM* model. $MAWT - WT$ is plotted against time. At the beginning of the waiting phase, $MAWT = AWT$ and the waited time is $WT^i = 0$. When $MAWT - WT$ is equal to 0 the pedestrian crosses. The *MAWT* may increase or decrease depending on the situation, but the threshold *PT* limits the possible increase. If *MAWT* reaches the threshold (red curves), it does not seem to decrease after that. This is probably due to situations where many pedestrians are waiting, leading to a consistent positive influence. In some cases, pedestrians almost takes the decision to cross (low values of $MAWT - WT$) but then $MAWT - WT$ increases. In other cases, the decrease becomes stepper because more pedestrians are crossing, and influence those who are waiting. Unfortunately, this situation is difficult to compare to real data.

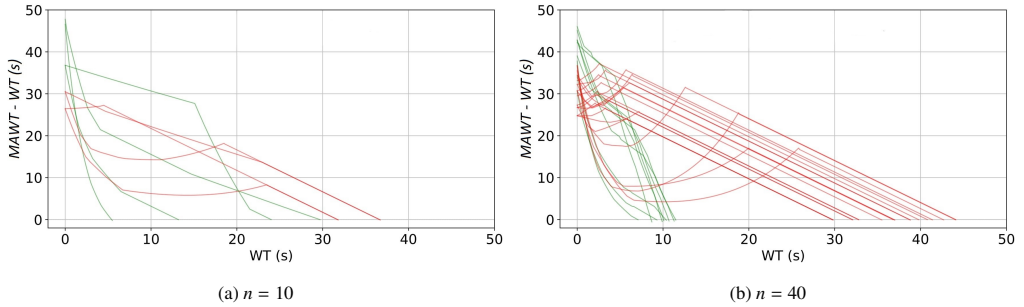


Fig. 9: Evolution of the MAWT for pedestrians who cross at a red light. Population H with $n = 10$ (left) and $n = 40$ (right), with $p_W = 0.9$, $p_C = 0.1$ and $PT=120\%$. Curves are in red when the MAWT reaches the individual threshold T before the illegal crossing.

Fig. 10 compares the waited time and arriving time of agents crossing at red lights, for all simulations with the Social Influence Model. Most of them arrive during the first 10 s of the red light, which makes sense since they waited longer than the rest of the agents. They start to violate after 5 to 45 s of waiting, which is interesting because the distribution of AWT was bounded in these simulations to values above 20 s. Thus, some agents have been influenced negatively to cross. Some authors found that the longer the pedestrians wait, the more they violate the rule [Ullman et al., 2004, Guo et al., 2011].

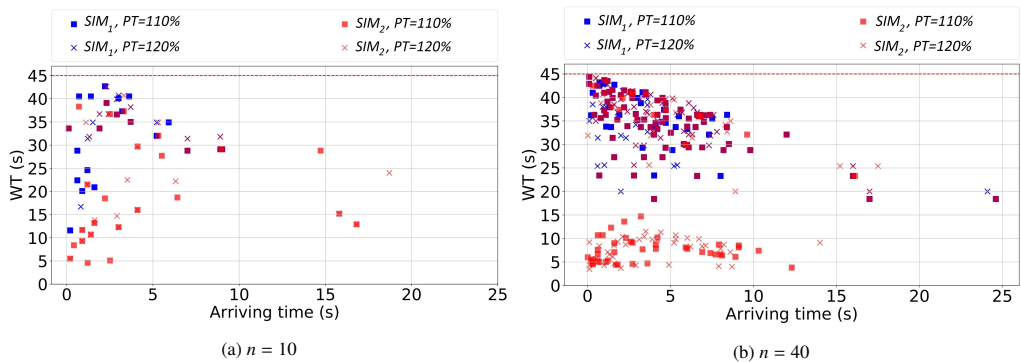


Fig. 10: Comparison between the waited time and the arriving time during the red light for simulated pedestrians crossing at the red light, for all simulations. Blue marker (resp. red) corresponds to simulations with $p_W = p_C = 0.5$ (resp. $p_W = 0.1$ and $p_C = 0.9$). Square marker (resp. crosses) is for $PT=110\%$ (resp. 120%). The horizontal red line on top is the duration of the red light. Left: $n = 10$ agents; Right: $n = 40$.

The accepted waiting time distribution is different with $n = 10$ and $n = 40$. When $n = 10$, the waited time is distributed between 5 and 45 s. When $n = 40$, it is clustered in two modes, around with 7s and 37 s. This is consistent with results from Lipovac et al. [2013] where most violations happen at the beginning and at the end of the red light. Ullman et al. [2004] and Guo et al. [2011] found that pedestrians become impatient after waiting a long time.

6. Discussion

A Social Influence model of the crossing decision has been demonstrated as a proof-of-concept that social influence, which is a known factor contributing to pedestrian crossing decision, can be included in simulation models. The proposed model uses theoretical priors based on psychological science results, and a small number of parameter which needs to be tuned to experimental data. Indeed, the production of experimental or observational data is a key factor in the future usefulness of the proposed model – and of any other pedestrian crossing models.

The proposed model being a proof-of-concept, all parameters need further investigations for a better tuning. This concerns the values of the Accepted Waiting Time, the weights p_W and p_C , and the number of pedestrians that a pedestrian can perceive. Moreover, some factors that have not yet been considered deserve some investigations: for instance, the pedestrian's social status and distance. Moreover, for real time applications (such as Virtual Reality), additional developments are needed.

Parameters. Due to the lack of individual data on social influence, p_C and p_W were defined as global parameters. It would be interesting to estimate these parameters (mean and variance) in laboratory experiments and conduct simulations with a population of agents who would have different influence sensitivities.

Perceived pedestrians. In the simulations, the perception was limited to 10 neighbors, mimicking human processing limitations [Saaty and Ozdemir, 2003]. The selection of these neighbors was based on their positions. But if more neighbors are waiting on the sidewalk and the waiting neighbors are closer than the crossing neighbors, a pedestrian may not see those who are crossing, which seems counter-intuitive. A perspective would be to use a meta-agent, similar to one developed by Lemerrier and Auberlet [2016] for group collision avoidance. Several agents would be considered as one group, allowing the perception of more than 10 neighbors while taking the human processing limitations into account. In addition, the distance to the neighbors may also impact their influence, as well as the familiarity [Faria et al., 2010]. Moreover, we have only considered one crossing direction; given that pedestrians coming across from the opposite side may reduce the cautiousness [Harrell, 1991], an interesting perspective would be to use the proposed model to simulate bidirectional pedestrian street crossings.

Social status. To simplify the model, we have limited the influence to the neighbor's states (crossing/waiting). To enrich the model, other factors could be considered. Lefkowitz et al. [1955] and Guéguen and Pichot [2001] found that the social status of others impacts their influence. Lefkowitz et al. [1955] hypothesized that high-status persons who violate the rules influence more, leading to more violations, than low-status persons. Conversely, high-status persons who wait leads to more people who conform to the rules. Their experiments confirm the first hypothesis, but not the second, since the compliance to the traffic rules was already high in the second scenario. Their results could mean that the influence from crossing or waiting neighbors might not have the same importance. Guéguen and Pichot [2001] conducted an experimentation in a street with low traffic volume and few risks for pedestrians. They found that higher violations for a high-status compared to the control group, and the opposite for a low-status. Future work should investigate weighting the importance of each pedestrian depending of their perceived social status.

Real time. The time step has an impact on the results, because the time course of the accepted waiting time depends on the time step value (see Eq. 2 and 3). Thus, the model cannot be implemented in real time, where the time step can be different at each step. This issue can be resolved using a new function in Eq. 2 where the time step is explicitly considered [Rakotoarivelo et al., 2021].

7. Conclusion

According to Rosenbloom [2009], seeing someone crossing or waiting at a red light influences our crossing decision. The contribution of this work consists of computing a social influence parameter to modulate the individual accepted waiting time (MAWT) in pedestrian crossing simulations. The proposed model allows the MAWT to increase, let pedestrians agents wait longer than if they were alone, or to decrease and let them wait shorter than if they were alone. This Social Influence Model (SIM) simulates pedestrians agents supposed to cross at the red light and waiting for the green light, influenced by waiting neighbors to stay at the kerb. Conversely, neighbors crossing at the red light encourage the agent to cross during the red light. Moreover, agents with similar characteristics and perceiving the same situation (color of the pedestrian light and the behaviors of their neighbors) but arriving at the crossing location at different times may take different crossing decisions due to the different amount of time elapsed since they arrived. The behaviors produced in the simulations are consistent with those observed in the literature, regarding the violation rates and the waited time.

The SIM is pretty simple regarding its formulation. It uses a linear combination of the number of neighbors of each state (waiting/crossing) to compute the social influence, and nevertheless produce heterogeneous crossing behaviors, which can be observed and compared to real behaviors. The model is modular regarding its implementation. It was demonstrated with ORCA as its navigation model, but we expect similar results with other navigation models, such as a SFM.

How can we interpret the social influence effect in pedestrian crossing? Some pedestrians may think that if someone is crossing, then it is safe for them too [Faria et al., 2010]. Knowing that someone is breaking the rules increases the likelihood of infractions [Lefkowitz et al., 1955]. This can create a cascade of decisions not adapted to the situation, starting from the decision of one person [Faria et al., 2010]. Harrell [1991] suggested that pedestrians delegate responsibility to a group and that they are more cautious alone. In some situations, pedestrians use other people as a cue and do not look at the pedestrian light [Harrell, 1991].

In the proposed model, the main limitation for future applications is that interaction with cars is not taken into account. An important step in the near future will be to allow pedestrians agents to interact with road traffic, and thus to embed the proposed Social Influence Model in a pedestrian-vehicle interaction model of the crossing decision. A pedestrian might be influenced by the crossing neighbors, but also needs to consider the oncoming traffic, leading to a trade-off. Including social influence in pedestrian-vehicle interaction models would allow useful applications of the model to emerge.

The most important among these applications would be allowing simulated pedestrians to be sensitive to social influence in virtual reality applications dedicated to the learning of road crossing. Indeed, Tolmie et al. [2002] developed a computer-based training application for street crossing for kids. They demonstrated “the potential of computer-based training, although the evidence suggests its value is as a support mechanism and as a complement to, not a substitute for, roadside training”. Benefits are found for two of the main skills involved in the street crossing tasks: “roadside search” and “gap timing”. Their results suggest that street crossing models can

be used as a tool to train people in virtual environments, and more specifically, our model may be integrated in a VR tool for training people to cross [Schwebel et al., 2008], more realistically than what is usually done in terms of rule compliance [Rakotoarivelo et al., 2021].

Considering that pedestrian agents can influence humans in VR environments, our model may also be useful for the experimental study of human behavior in the lab. For instance, Morrongiello et al. [2018], Jiang et al. [2018] have conducted paired crossings between a participant and a real human or a computer-generated agent partner. In Jiang et al. [2018], the crossing scenario included road traffic, and the partner has either a safe or risky behavior in terms of gap selection. In this experiment, the participants adapted their behavior to their partner's behavior, but the external validity of such experiments would probably benefit from a model where the simulated pedestrians are sensitive to social influence.

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Appendix A. Abbreviations table

AWT	Accepted Waiting Time	agent parameter
MAWT	Modified Accepted Waiting Time	variable
ORCA	Optimal Reciprocal Collision Avoidance	model
SFM	Social Forces Model	model
PT	Percentage Threshold	agent parameter
SIM	Social Influence Model	model
WT	Waited Time	variable
WTM	Waiting Time Model	model