Visual cues in pedestrian's crossing decision: in search of a quantitative model.

Roland Brémond
Université Paris-Est, IFSTTAR, IM, LEPSIS, F-75732, Paris, France
roland.bremond@ifsttar.fr

Ariane Tom
Université Paris-Est, IFSTTAR, IM, LEPSIS, F-75732, Paris, France
arianectom@yahoo.fr

Lara Désiré
CETE Ouest, LR Saint-Brieuc, ERA33 F-22015, Saint-Brieuc, France,
lara.desire@developpement-durable.gouv.fr

Elodie Gigout
IFSTTAR, MA, F-13300 Salon de Provence, France
elodie_gigout@yahoo.fr

Marie-Axelle Granié
IFSTTAR, MA, F-13300 Salon de Provence, France
marie-axelle.granie@ifsttar.fr

Jean-Michel Auberlet
Université Paris-Est, IFSTTAR, IM, LEPSIS, F-75732, Paris, France
jean-michel.auberlet@ifsttar.fr

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ABSTRACT

The simulation tools of people's displacements become more and more popular for applications emerging in the field of mobility planning, traffic management, impact assessment for city design and infrastructure modifications. Moreover, there is a lack of computational tools for the microscopic simulation of urban interactions between drivers and pedestrians. Feeling that road crossing is currently the main problem with pedestrian behavioural models, we conducted a laboratory experiment in order to understand to what extend the pedestrian's visual environment contribute to the crossing decision in order to improve a computational street crossing model. In the experiment, 36 12-second-video clips were presented to 32 participants, in conditions close to the crossing situation (scale 1, 160° of angle displayed on 6 large screens). The subjects were asked if they would have cross the street at the end of each clip. Two hypotheses were under investigation. The first one focuses on the objective description of the road crossing environment in terms of visual cues relevant for the crossing decision (traffic light, approaching vehicles, other pedestrians, etc.). The subject's answers were compared to the coding of the visual environment. The second hypothesis focuses on the subject's own explanations, about their motivations for crossing / not crossing. In both cases, the statistical analysis (logistic regressions) suggests that the crossing decision does not use the same visual cues depending of the presence/absence of traffic lights. The main result of this study is that the relevant visual cues are not the same at the signalized and at the unsignalized crossing, which leads to build separate quantitative models.

Keywords: pedestrian, road crossing, experimental psychology.

INTRODUCTION

The “digital city” is a growing challenge for many actors of urban planning, raising new issues to the field of numerical simulation. One promising aspect is the numerical simulation of people’s displacements inside a city with applications emerging in the field of mobility planning, traffic management, impact assessment for city design and infrastructure modifications. One of the associated scientific challenges is to propose realistic computational models of the pedestrian’s behaviours. Although a number of commercial applications are available for traffic simulation on the one hand (Aimsun®, Corsim®, Paramics®, Vissim®...), and for crowds simulation on the other hand (Legion®, SimWalk®, (*1*)), very few simulation tools include both cars and pedestrians (*2*). The simulation of their interactions in road crossing is a major problem for a complete urban traffic simulation.

In their review on pedestrian’s crossing decision models, Tom et al. (*2*) concluded that available computational models are not suited for this task, first because the pedestrian/driver interactions are only weakly considered, second because very few pedestrian’s skills are taken into account in these models (*3*, *4*, *5*, *6*, *7*). Indeed, in accordance to Grayson (*8*), the road crossing task is made up of three steps, the second one, itself made up of three steps in accordance to Tolmie *et al.* (*9*), are briefly the following:

- step 1: choice of the area for the street crossing
- step 2: choice of the time to cross
    - step 2.1: exploration of the visual space;
    - step 2.2: selection of the relevant information ;
    - step 2.3: analysis of the situation based on the estimation, of the time to collision, the distance to the conflict point...;
    - step 2.4: decision to cross or not
- step 4: the road crossing as a motor task, The risk of accident arises during this phase.

Most of the existing road crossing models are only based on the studies which focus on both steps 2.3 and 2.4.

Moreover, Kitazawa and Fujiyama (*10*) claim that most pedestrian computational models use what they call the Information Process Space (IPS): the area around the pedestrian where s/he picks up information in order to compute where to move next. This area may be considered as a component of the pedestrian’s perceptive skills, and the authors showed that the IPS, which may be thought to as a visual attention area, is included in most computational pedestrian models (*3*; *4*, *5*). But models are not made for the road crossing studies since only pedestrian/pedestrian interactions and pedestrian/infrastructure interactions are considered.

A simulation approach needs some inputs from behavioural science in order to implement the pedestrian’s and driver’s behaviour. A number of such models have been proposed, both for pedestrians (*3, 4, 7*) and drivers (*11*, *12*). The interactions between these two types of actors have been addressed in psychological studies, with two main approaches: gap acceptance (*13*) and rule compliance (see (*14*) for a review). Very few studies have addressed so far the complexity of road crossings, and computer simulations are far from realistic there, considering the road crossing decision.

Furthermore, Tom et al. (*2*) have suggested that a more relevant computational model of pedestrian could be built on a Multi-Agent System (MAS), where each pedestrian would have his/her own perceptive, cognitive and anticipative skills. This would imply a computational model of information taking, as in (*15*), including some perceptive limits (*16*; *12*).

One of the objectives of this works was to improve the road crossing models for such simulation tools. In many models, street crossing models are very simple from a psychological point of view, comparing the time gap offered by the traffic flow to an estimation of the pedestrian's crossing time (Steps 2.3 and 2.4). Commonly, modellers use an equation in the following form:

$$Time\_Headway > a * (Safety\_Margin + Estimated\_Crossing\_Time) \quad (1)$$

where

$$Estimated\_Crossing\_Time = Road\_Width / Pedestrian\_Desired\_Speed \quad (2)$$

where the Time_Headway is the time between two successive vehicles, the Safety_Margin takes into account the reaction time, the time to start and a safety margin (it varies between 2 and 4s in the Highway Capacity Manual) and “a” is a parameter to illustrate the aggressive/prudent behaviour of the pedestrian.

If (1) is true, the pedestrian crosses, otherwise he waits for a new gap. In future work, we consider replacing the parameter “a” with outputs from a quantitative psychological model, taking better into account pedestrian perceptual and cognitive skills (steps 2.1 and 2.2).

For instance, what visual cues pedestrian selects and takes into account has seldom been studied (*9*) and this key factor of crossing decision is then not implemented in models (*3*). With goals to better understand what visual cues in environment are used by the pedestrians in their crossing decision, and to take this into account in a pedestrian model, we have designed a laboratory experiment, in order to get realistic road crossing situations, whilst controlling the experimental parameters. We developed a new experimental setup (*17*, see Figure 1a), where videos taken from urban road crossings, from the point of view of a pedestrian facing the crossings. The videos were displayed at scale 1 in a Virtual Reality room, with more than 160° of display angle, and spatial sound (see Figure 1b). The subjects were asked, after each video clip, if they would have crossed the street at the very moment when the clip ends. This “Crossing decision” was the variable to explain.

Two approaches were considered. First, each video clips were coded with visual cues which were found a priori relevant for the crossing task decision, and statistical models tested whether these objective variables could explain the subject's Crossing decision. This was the “objective” approach. Second, just after their Crossing decision, the subjects were asked to explain their reason for crossing or not, and the visual cues which were mentioned in their justification were also coded. The visual cues the subjects mentioned were also considered as independent variables to explain the crossing Decision. This was the “subjective” approach.

MATERIAL AND METHOD

Video Clips

Forty-one panoramic video clips of 12 seconds each were selected for this experiment. First, 3 videos of one hour each were taken at 3 road crossings in Paris, France. The video capture system (*17*) was facing a crossing area. As the panoramic system was limited to 160° (compared to 360°), the street behind the central camera did not appear in the videos. Thus, it was decided as a criterion in the crossroads selection that this street behind the camera should be one-way (vehicles coming in front of the subjects). Crossroads C1 (Convention/Saint-Charles, named after the streets' name) and C2 (Ledru-Rollin/Charenton) were regulated by traffic lights, while crossroads C3 (Championnet/Poteau) was not. The annual mean traffic at these intersections is 7595 vehicles/day at C1, 7185 at C2 and 4183 at C3. Five clips from Crossroads C1 were selected for the habituation phase of the experiment, and 18 clips were selected of each of C2 and C3.

Experimental Protocol

Thirty-two participants took part in this experiment. All participants were recruited at the IFSTTAR, and reported that they had no visual, hearing, or vestibular deficiencies. They all signed an informed consent form. Still, technical problems emerged during the experiment due to voice recording issues (n = 8) and a clip presentation issue (n = 1). As a result, 23 participants were included in the data analyses, 15 men and 8 women (mean age: M=35.17; SD=12.88). A short questionnaire at the end of the experiment revealed that all participants were unfamiliar with the experimental crossroads.

(a) (b)

FIGURE 1 Virtual reality acquisition (a) and display setup of 162° videos, at scale 1 (b)

The experiment took place in a Virtual Reality room at the IFSTTAR at Paris (France). The subjects faced 6 vertical screens of 2 meters high each, in order to display the 162° panoramic videos at scale 1 (see Figure 1b). The screens were joined together in order to form a half-circle. The video-projectors were linked with VGA cables to a PC equipped with 3 Go of RAM and a 3 GHz Intel® Core Duo processor. Their resolution was 1,400×1,050 pixels each, therefore the projected video on the 6 vertical screens had a resolution of 6,300×1,400 pixels. In order to stretch out this banner in full screen mode, we used the VLC free display software (www.videolan.org). Further, two Matrox® M9140 graphic cards were linked together, and the use of Matrox® Powerdesk software extended the PC desktop to 6 HD screens vertically flipped. Finally, the projection room was equipped with a Dolby 5.1 sound system.

The participants were instructed to “pay attention to each projected clip, because just after the projection (they) will have to answer to some questions about it”. They were also told that a picture, irrelevant to the experiment (clouds in the sky), would appear on the screens between two clips, and would stay there till they finished answering the questions, without any time limit to do so. Then, the participants were equipped with a digital voice recorder and a tie-pin style microphone. The digital voice recorder was an Olympus® DS 2000, equipped with a 64MB SmartMedia card. The experimenter generated a playlist via the computer, made up of the five training clips in a fixed order, and of the 36 experimental clips in a random order. In consequence, each participant watched a unique combination of the experimental clips. After each clip, questions were asked, in order to capture the subject’s crossing decision at the moment when the clip stops, and to collect verbal data about the visual stimuli relevant to their decision. Altogether, the experiment lasted about 1 hour per participant.

The participants’ verbatim were transferred to a PC via an appropriate card reader. Then, the experimenter listened to the audio files with the DSS Player software. Data were processed via the Statistica and PASW Statistics softwares.

Coding of The Video Clips

The 36 video clips of crossroads C2 and C3 were coded by an experimenter, independent of the verbal data collection. This coding used The Observer XT software (Noldus Information Technology).

The a priori classification of relevant visual items included various theoretical framework. First, due to potential conflicts (including the gap theory), the vehicles were coded if they could be considered as having a potential conflict with the subject, that is, if the vehicle was moving and could possibly cross the pedestrian's trajectory. Then, attention and workload were taken into account by coding the origin of the vehicles (from the left vs. from the right), as well as the vehicle's position at the end of the clip. The type of vehicles was coded: car, bus, truck, commercial vehicles, powered two wheels and bicycle. Due to social influence on crossing decision, the pedestrians crossing at the same pedestrian crossing than the participant, as well as their movement (crossing vs. static) and their crossing direction (same vs. opposite of the subject's direction) were also coded. Finally, to take rule compliance into account, the colour of pedestrian light was coded at the signalized intersection.

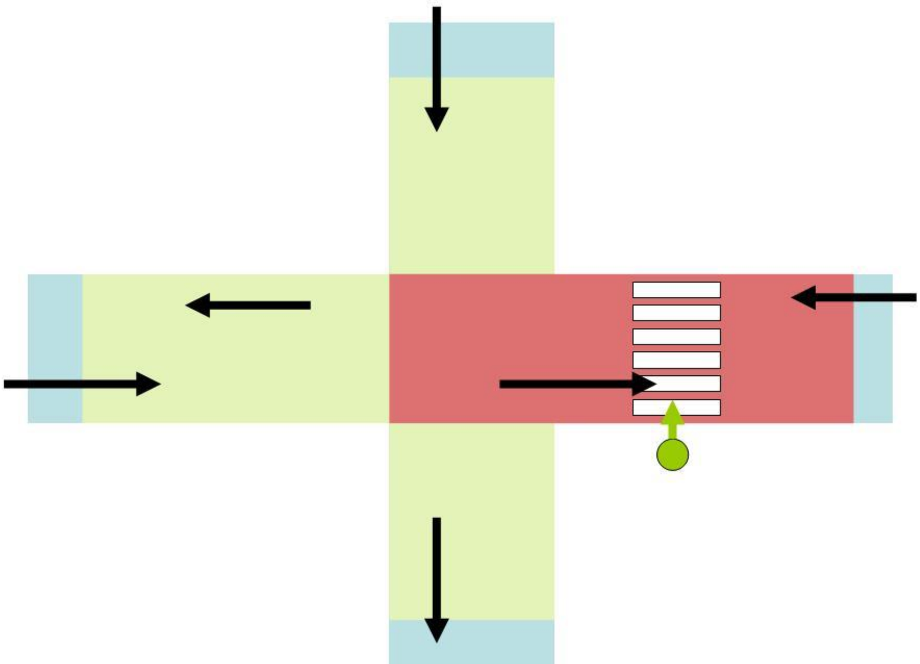

FIGURE 2 The near (in red) and far (green) coding areas, from the pedestrian's point of view (in green)

The coding was done in two steps. First, all a priori variables were coded, which resulted in 22 objective variables, describing the last second of each video clip. Then, a first data analysis helped us to merge some variables and dismiss some other, in order to improve the expected explaining power of the resulting variables over the Crossing decision variable. From the 22 variables in the first coding, 3 were dismissed because no occurrence was found in the available data (number of trucks, number of buses and number of vehicles situated on the road crossing at the end of the clip). The vehicle's position was simplified, with only two positions in the final coding: Near (already engaged in the crossroads, or coming from the right) and Far (not yet engaged) from the pedestrian crossing (see Figure 2). The pedestrians were distinguished only in terms of motion (static vs. crossing pedestrians).

Finally, the 11 selected objective binary variables were the following: No traffic light, Colour of pedestrian's light (only in the signalized crossroads), Vehicles on the Left, Vehicles on the right, Vehicles in the Far area, Vehicles in the Near area, Cars, Two wheels, Commercial vehicles, Static pedestrians, Crossing pedestrians. Note that some parameters were not taken into account, while they were expected to be relevant, because no tool was available in our lab for the coding. It is the case, for instance, for the vehicle's speed.

Coding Of The Subject's Answers

A first series of predictor variables were defined on the basis of the content analysis of the verbal justifications. To do so, all visual landmarks mentioned by the participants were extracted from their verbal productions. Some were then grouped together, on the basis of their identity or identical meanings in order to form a category (cognitive landmarks, in the sense of Sorrows and Hirtle, *18*). Eventually, we counted a total of 15 categories to justify one's crossing decision. Five visual cues were specific to the signalized crossroads and addressed the traffic light: Red man, Green man, Red light, Amber light and Green light. One was specific to the unsignalized crossroads, and explicitly mentioned the absence of traffic lights to explain the Crossing decision. Two concerned the pedestrians: Single Pedestrian, and Group of pedestrians. Five items referred to the traffic, either directly (Traffic) or in terms of vehicle type (Truck/Bus, Car, Powered two wheeler, Bicycle). More variables were included, one for Infrastructure (Crosswalk, Road surface, etc.), and one for Sounds.

Finally after a similar analysis for the first coding of the video clips, the coding was merged into 8 independent variables: Crossing signals (Green man, red light), Not crossing signals (Red man, green light, orange light), Group of Pedestrians, Single pedestrian, Single vehicle, Traffic, Absence of signalization (in the unsignalized crossroads) and Infrastructure.

RESULTS

One preliminary result concerns the rule compliance in experimental environments. The rate of illegal behaviour at the signalized crossroads (crossing when the traffic light is green) was 26%. Although the video clips are not supposed to be representative of crossroads situations, this value can be compared to non-compliance rates of 10 to 25% in old observations in France (*19*), 7 to 14% in recent observations on sites with two lanes in Montreal, Canada (*20*) and 13% in recent observations in Israel (*21*). This comparison is interesting with respect to the desirability bias, which is common bias in experimental psychology: subjects tend to answer what they expect the experimenter wants to hear. In the current experiment, we could fear that people would be more compliant than they are in real life. The high non-compliance rate cited above suggests that this is not the case, and that the experimental setup is relevant to investigate crossing decisions.

Statistical Analysis

The experimental data finally included 23 subjects and 36 clips, which results in 828 Decisions (414 for the signalized, and 414 for the unsignalized crossroads). Statistical analyses used the Crossing decision as the dependent variable (to be explained). The first series of analyses considered the objective (video coding) variables as independent variables, and is referred to as the "objective" model. The second series considered the verbal justifications as independent variables, and is referred to as the "subjective" model.

To explain the Crossing decision, two binary logistic regressions were computed for the two sets of explaining variables (objective and subjective). The models were computed with the SPSS software, using the likelihood descendent algorithm for selecting the variables which increase the discriminatory power of the model about the Crossing decision. The main output indexes were the model's prediction (from the confusion matrix), and Nagelkerke's R2 estimate, and Wald's p-value.

Table 1 shows the model's selected variables, along with their coefficient and their p-values. This model leads to 70.3% of correct predictions. The estimated R2=0.285 is quite low. Surprisingly, the global model based on subjective variables (Table 2), which was expected to be closer to the actual decisions, only predicts 58.0% of the crossing decisions (with an estimated R2=0.051, which is very small, and even smaller than the "objective" model). This result could be explained by the number of variables involved in the models (8 for the objective model and 4 for the subjective model).

TABLE 1 Model Computed from the Objective Variables, from a Binary Logistic Regression. Incentive variables are in Green, Inhibitive Variables are in Orange

	Coefficients	p
Constant	4.347	0.000
Pedestrian red light	-4.314	0.000
No traffic light	-3.152	0.000
Cars	-0.939	0.000
2 wheels	-0.837	0.000
Vehicles from the right	-0.518	0.004
Static pedestrians	-0.387	0.009
Vehicles in the far area	0.922	0.001
Crossing pedestrians	0.282	0.003

TABLE 2 Model Computed from the Subjective Variables, from a Binary Logistic Regression

	Coefficients	p
Constant	-0.500	0.008
Single pedestrian	-0.686	0.015
'No cross' signal	-0.266	0.081
Single car	0.300	0.003
Group of pedestrians	0.436	0.006

The low quality of these models and the weight of visual cues only present at signalized crossroad suggest that better models for Crossing decisions should emerge by distinguishing analysis for signalized and unsignalized crossroads.

Separated Objective Models

Separate data analyses were performed on signalized and unsignalized crossroads. As only one site of each crossroad type was present in our data, difference between the two situations could be related to the site specificity (including the level of traffic) or to the presence of traffic light. However, for practical applications in urban planning, these two factors (site and signalization) are not independent; conversely, the selected sites were selected with the criteria that they were typical (in the sense of urban planning) of signalized and unsignalized crossroads in Paris.

First, binary logistic regressions were performed on the data with decision to cross as the dependent variable and variables from the video coding as predictor variables. Two separate regressions were computed separately, for the signalized crossroads, and for the unsignalized one.

Signalized Crossroads

For the signalized crossroads, 6 from the 10 explicative variables are significant predictors of the computed "objective" model of Crossing decision (Table 3): Crossing pedestrians is the only incentive variable, while Pedestrian red light, 2 wheels, Static pedestrians, Near position, and Cars are all inhibitive variables. The model's variables and p-values are given in Table 3. The R2 value is 0.456, meaning that the model better explains the probability of the Crossing decision than the previous global model. From the confusion matrix, the predictive power of this model is 80.4 %, which is also much better than previously.

The polarity of the variables in Table 3 is as expected, and the traffic light appears as the main quantitative variable. Static pedestrians inhibit the Crossing decision, while pedestrians crossing in the same time encourage it.

TABLE 3 Model Computed from the Objective Variables at the Signalized Crossroads

	Coefficients	p
Constant	4.678	0.000
Pedestrian red light	-4.286	0.000
2 wheels	-0.918	0.004
Static pedestrians	-0.865	0.001
Near position	-0.715	0.011
Cars	-0.454	0.044
Crossing pedestrians	0.472	0.001

Unsignalized Crossroads

For the unsignalized crossroads, 5 from the 9 explicative variables are significant predictors of Crossing decision in the computed model (see Table 4): Cars, 2 wheels and vehicles coming from the right are inhibitive variables, while Vehicles in the Near and the Far areas are incentive variables. There is no paradox here: a vehicle in the Far area brings a positive coefficient (+2.688), but consider it's a car and it comes from right, it also brings two negative coefficients (-2.154 and -1.149), with a negative (inhibitive) result.

TABLE 4 Model Computed from the Objective Variables at the Unsignalized Crossroads

	Coefficients	p
Constant	1.367	0.000
Cars	-2.154	0.000
2 wheels	-1.127	0.001
Vehicles coming from the right	-1.149	0.000
Vehicles in the near Area	0.756	0.015
Vehicles in the far area	2.688	0.000

The R^2 value is 0.134, meaning that the model weakly explains the probability of the Crossing decision. The predictive power of this model is 57 %, which is poor, even compared to the Global objective model. This result suggests that the Crossing decisions at the unsignalized are hard to explain from a rough description of the pedestrian's environment only.

Discussion on Objective Models

Predictive model on crossing decision at signalized crossroads shows that crossing pedestrians encourage decision to cross. This may be due to social influence (people tend to follow each other, or to mimic other people when they don't cross), but another explanation is possible: as the model is descriptive rather than explicative, it may happen that Crossing decision of all the pedestrians depends on the same variables. In this case, a correlation would also be expected. The statistical analysis of the subjective data, below, will show that the pedestrians influence the Crossing decision since the other pedestrians behaviour is cited among the visual cues relevant to take a Crossing decision in the case of signalized and unsignalized crossraods (see below Table 6).

For the predictive model of Crossing decision at unsignalized crossroads, it should be noted that, although the model is not very predictive, the other pedestrians are not included in the model's variable. This may be seen as an unexpected result, as one could have guessed that in the absence of mandatory rule (due to the traffic lights), the crossing decisions could more depend on the other's behaviour (social influence).

When comparing the explaining variables for the two "objective" models, it is clear that these two kinds of crossroads do not lead to the same Crossing decision mechanisms: only two variables (Cars and 2 wheels) play the same role at both crossroads. This result confirms the fact that looking for a global Crossing decision model, irrespective of the crossroad type, is not realistic.

From the above data, the quantitative model of the Crossing decision is not very useful for microscopic simulations of the unsignalized crossroads, due to the low predictive power of the model. The situation is better on the signalized crossroads, where the normative behaviour (negative correlation with the pedestrian red light) leads to a much better prediction.

Our understanding of these results is twofold. First, one may think that the individual Crossing decision cannot be derived only from the objective description of the surrounding environment, and individual factors are expected to play a role as well. This is obvious, looking at the Crossing decision data: on each video clip, a certain amount of subjects decide to cross, while the remaining does not. Hence, their decision cannot be explained by their environment alone, as they experienced the very same traffic scenes (subjects should cross at 46% (+/- 13%) of the crossroads).

The second observation is that one may discuss the relevance of the proposed explaining variables, and suggest new and more relevant variables. For instance, we have mentioned earlier the vehicle's speed, which was not available in the present study, and which may have contributed to the subject's Crossing decision. Such new objective variables may be included in a future work, and image processing techniques would help here, in order to estimate the cars and pedestrian's speeds from the video clips.

Separated Subjective Models

Signalized Crossroads

Binary logistic regressions were computed from the verbal justification of the Crossing decision at the signalized and unsignalized crossroads separately. Table 5 shows the model computed for the signalized crossroads. The R^2 value is 0.103, meaning that the model weakly explains the Decision to cross. From the confusion matrix, the predictive power of this model is 65.2 %, which is a little better than using the previous global subjective model, however not much.

TABLE 5 Model computed from the subjective variables at the signalized crossroads

	Coefficients	p
Constant	-0.671	0.000
Single pedestrian	-1.535	0.014
No cross signal	-0.383	0.083
Infrastructure	0.459	0.062
Single vehicle	0.535	0.000

Four factors are significant to explain the Crossing decision: the mention of a single pedestrian and the pedestrian red light are inhibitive factors, while infrastructure elements and presence of a single vehicle are incentive factors. The polarity of these factors suggests that the participants mentioned the presence of another pedestrian in order to explain their Decision not to cross, and mentioned specific cars in the videos in order to explain their Decision to cross (e.g. about its low speed, etc.). Unfortunately, the classification of the subjective coding does not allow testing these hypotheses at this stage.

Looking at the model itself, the most striking result is that the "No cross signal" (red man or green light) is included in the model, however with a small contribution (-0.383) and a p-value above 0.05. The "Cross signal" (green man, red light) is not included. This can be compared to objective data, where the traffic light's colour is the main predictor of the crossing Decision. The comparison suggests that the Crossing decision actually depends on the colour of the traffic light, whereas the participants focused on other factors.

Unsignalized Crossroads

For the unsignalized crossroads, only 3 factors were significant (Table 6), all incentive of the Decision to cross: Absence of signal (allowing crossing, because it is not forbidden), Traffic and Single pedestrian. Note that pedestrians are used here to explain the Crossing decision, while they were used to explain the not crossing decision at the signalized crossroads.

TABLE 6 Model computed from the subjective variables at the unsignalized crossroads

	Coefficients	p
Constant	-0.456	0.004
Absence of signal	0.820	0.020
Traffic	0.408	0.050
Single Pedestrian	1.185	0.000

The R^2 value is 0.108, meaning that the model weakly explains the Decision to cross. The predictive power of this model is 62.3 %. These values are higher than with the global subjective model, and of the same order of magnitude as for the signalized crossroads. This is another unexpected result: while the regression model is much better, with objective data, at the signalized crossroads, this difference does not hold with the subjective data.

Comparing the two subjective models, the striking result is that no variable have the same contribution in the two models. This definitely confirms our hypothesis that the Crossing Decision does not use the same kind of visual cues at the two kinds of crossroads, or does not use them in the same way.

DISCUSSION

Several results emerge from this work. First, quantitative models are proposed in order to predict the pedestrian's crossing decision at a crossroads, for people unfamiliar with this crossroads. The so-called "objective" models, based on a description of the pedestrian's environment, allow an easy implementation in a microscopic traffic simulation. The "subjective" ones, based on the subjective report of the subject's motivation to cross, are not so easy to implement, because no model of information selection is proposed here, and this is the subject of a future work. The first step in this direction would be to understand what items are present in the environment, and not reported in the Decision's motivation.

Second, both approaches show a strong difference between signalized and unsignalized crossroads. Of course, traffic lights explain this difference, being a major explaining variable in both the objective and subjective models. However, one cannot say that the difference is only due to traffic light. As the selected crossroads were typical of signalized and unsignalized crossroads in Paris, the difference may describe the urban crossroads typology rather than the presence/absence of traffic lights, and further studies are needed with more crossroads, in different cities and countries.

The signalized crossroads leads much better predictive models of Crossing decision, both by objective and subjective variables, than the unsignalized one. The fact that objective variables can hardly explain the decision at unsignalized crossroad is related to the absence of normative behaviour with respect to the traffic lights, but it also shows that no socially shared implicit rules replace the explicit legal rules. Thus, one may guess that the subjects are more likely to use individual strategies. Moreover, these strategies seem unavailable through the verbal data, as the justification people give to explain their behaviour is weakly correlated to the effective Crossing decision. This second and important result suggests that the crossing strategy, at unsignalized intersections, is mostly automatic and non conscious, compared to what happens at signalized crossroads.

The objective models are always better, in terms of behaviour prediction and for fitting the real probabilities but also more complex (as there are more variables). This result is puzzling, and one explanation may be that verbal justification, posterior to the crossing decision, is more a re-construction of the decision than the decision itself. This result needs further research, because it suggests (as we have just proposed) that the Crossing decision is mainly non conscious, that is, guided by automatic processes, even in an experimental setup such as the one which is used here.

Our work in the present paper may also be seen as a direct contribution to traffic simulation models, which is one of our initial objectives, as it includes a quantitative implementation of the crossing decision, with the regression models. Our results suggest separated models between two situations, signalized and unsignalized crossings. The so-called "objective" models seems more useful than the "subjective" models for a first practical implementation. Indeed, the structure of the objective models is easier to implement, as the objective variables can be computed from the pedestrian's spatial environment. But the perception of the environment by a simulated pedestrian with the objective model could be considered as determinist (visual cues are present or not). Moreover, many research show that perception is an individual process, and in this way the subjective model allows us to build a non determinist model.

For a practical implementation, it should be noted however that Lobjois and Cavallo's results (*22*) suggest that the decision to cross may be overestimated in our model, due to the fact that the subjects did not actually cross the virtual street in the experimental condition. A quantitative evaluation of this possible overestimation would need new experiments.

Future work is also needed for a better understanding of the decision to cross. Of course, our results need to be confirmed in more situations, with various kinds of traffic lights and road crossing designs. This would lead to a classification of road crossings, on the basis of the visual landmarks pedestrians use in order to make their crossing decision. Another important issue would be to propose a new methodology to understand the relevant visual landmarks, given that verbal data were very weakly correlated to the Crossing decision.

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