Article

Evaluating Pedestrian Interaction Preferences with a Game Theoretic Autonomous Vehicle in Virtual Reality

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Abstract: Localisation and navigation of autonomous vehicles (AVs) in static environments are now solved problems, but how to control their interactions with other road users in mixed traffic environments, especially with pedestrians, remains an open question. Recent work has begun to apply game theory to model and control AV-pedestrian interactions as they compete for space on the road whilst trying to avoid collisions. But this game theory model has been developed only in unrealistic lab environments. To improve their realism, this study empirically examines pedestrian behaviour during road crossing in the presence of approaching autonomous vehicles in more realistic virtual reality (VR) environments. The autonomous vehicles are controlled using game theory, and this study seeks to find the best parameters for these controls to produce comfortable interactions for the pedestrians. In a first experiment, participants' trajectories reveal a more cautious crossing behaviour in VR than in previous laboratory experiments. In two further experiments, a gradient descent approach is used to investigate participants' preference for AV driving style. The results show that the majority of participants were not expecting the AV to stop in some scenarios, and there was no change in their crossing behaviour in two environments and with different car models suggestive of car and last-mile style vehicles. These results provide some initial estimates for game theoretic parameters needed by future AVs in their pedestrian interactions and more generally show how such parameters can be inferred from virtual reality experiments.

Keywords: Autonomous Vehicles; Pedestrian Crossing Behaviour; Interactions; Game Theory; Human Factors.

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1. Introduction

The widely predicted arrival of autonomous vehicles (AVs) on the roads poses several concerns regarding their future interaction with other road users, in particular with pedestrians. Unlike static objects in the environment which can be mapped and routed around by an AV, pedestrians are active and interactive agents, who move around to actively obtain their own goals and also interactively in response to the AV's own actions. Pedestrians can now be detected and tracked quite reliably Camara et al. (2020a) but modelling and controlling interactions with them remains an open question Camara et al. (2020b).

Recent trials of autonomous minibuses in European cities Madigan et al. (2019)[1] has shown that pedestrians can easily take advantage over AVs: these autonomous minibuses were programmed to stop when any pedestrian stepped in front of them. After a few days observing the AV's behaviour, some pedestrians appeared to learn this safety feature and started stepping intentionally in front of the AV, with instances of this behaviour occurring around once every three hours. Human drivers would not allow this to occur and would instead usually control their vehicles in ways to suggest some threat to such pedestrians, interacting with them to encourage them to get out of their way. This inability of current AVs to similarly control this type of interaction is one of their biggest problems, known as the 'freezing robot problem' or 'the Big Problem with self-driving cars' Brooks (2017). To make progress towards creating suitable AV interaction controllers, we thus recently proposed a game

[1] https://www.youtube.com/watch?v=PUr8ljfb2Cg

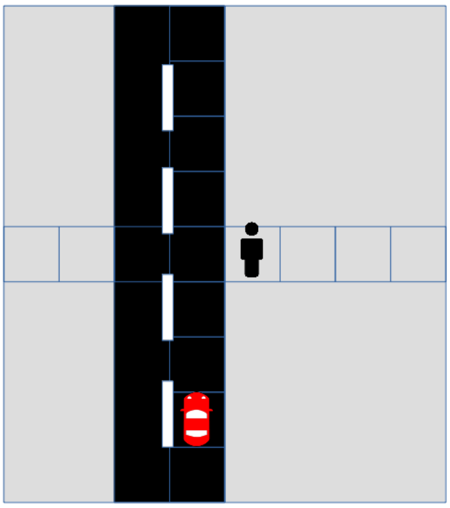

Figure 1. Two agents negotiating for priority at an intersection

theory model, called 'sequential chicken' for such interactions Fox et al. (2018), where a pedestrian encounters an autonomous vehicle at an unsignalized intersection, as shown in Fig. 1. Game theory offers a framework to model decision-making between rational agents, it has been widely used, for example, in Economics Morgenstern and Von Neumann (1953) and for coordinating multi-robot systems Meng (2008). We do not use conventional statistical analyses because they rely on a separation of cause and effect, or controlled and observed variables. But when studying interactions between agents, we inherently have both agents taking both roles, affecting one another, which is a better fit to game theoretic models than statistical methods.

After finding mathematical solutions to the model in terms of its free parameters, we then showed how the numerical values of its parameters can be fitted from empirical data. Unrealistic laboratory experiments were used to demonstrate this method. We first asked participants to simulate interactions in a board game in Camara et al. (2018b). Secondly, participants were asked to play the game in person moving on squares with a set of two speeds (SLOW, FAST) Camara et al. (2018a). Finally, participants played the game by moving continuously towards each other at their preferred pace Camara et al. (2020c). While providing a proof of concept of the method for finding parameters, these laboratory experiments showed unrealistic results, with participants preferring to save time rather than avoiding collisions in order to win what they perceived as games against the other player rather than protect their safety as they may value more in real life.

The present study aims to extend these experiments by applying the same parameter fitting method to new more realistic interaction scenarios. The new scenarios use virtual reality (VR) to enable a subject to interact with a game theoretic autonomous vehicle in the same road crossing scenario. VR offers the opportunity to experiment on human behaviour in simulated real world environments that can be dangerous or difficult to study, such as pedestrian road crossing, in which experiments need to explore human behaviour leading up to and during actual collisions between vehicles and pedestrians Deb et al. (2017); Hartmann et al. (2017). Virtual reality provides a much greater realism than the previous laboratory experiences, including a real sense of fear from being hit by the vehicle due to its apparent physical presence. These experiments are intended to show how more realistic game theory parameters can be recovered from VR interactions. These parameters could then be built into future AV software to help control their interactions with pedestrians, as well as providing interesting insight into pedestrian behaviour itself.

AVs are on their way not only to roads, but also to pavements in the form of autonomous last-mile robots used for urban delivery tasks de Groot (2019); Hoffmann and Prause (2018). Last-mile delivery vehicles are usually smaller than road vehicles, share the same pavements as pedestrians, and drive at lower speeds. To better understand this new and important use-case for AV interaction control, we also investigate participants' behaviour with these last-mile type vehicles to test if humans prefer to interact with them differently from on-road cars.

2. Related Work

This section gives an overview of related studies on pedestrian crossing behaviour and pedestrian–AV interactions using virtual reality, showing that previous work does not yet provide the game theoretic parameters of interest and thus motivating the new experiments.

2.1. Pedestrian crossing behaviour in virtual reality

In recent years, pedestrian crossing behaviour has been studied using virtual reality environments. In particular, VR has been used for teaching safe crossing behaviour to child pedestrians McComas et al. (2002); Schwebel and McClure (2010); Simpson et al. (2003). For example, Simpson et al. (2003) studied child and young adults crossing behaviour in VR, and recommended the use of VR for future studies in this domain. Other studies have focused on hazardous crossing situations such as Meir et al. (2015) where an investigation was carried on child and adult pedestrians' ability to detect dangerous situations while crossing in a virtual environment. The study showed that the awareness of hazardous situations increases with the age. Zito et al. (2015) studied older and younger adults crossing behaviour in a virtual environment. They recorded pedestrian behavioural data, such as their head and eye movement. Their results showed a safer crossing behaviour from younger adults and that older adults tend to look at the ground rather than the other side of the street. Doric et al. (2016) investigated pedestrian crossing behaviour and risk acceptance in a virtual environment. Their results suggest that VR creates realistic simulations and allows to test pre-crash events without injuries. Feldstein et al. (2016) studied pedestrian behaviour in critical crossing scenarios using presence questionnaires for gap acceptance analysis. Their results showed no significant difference between the crossing behaviour in their different scenarios. Schwebel et al. (2017) investigated distracted pedestrian behaviour in VR and at a real intersection. Their results showed that pedestrians self-reported a behavioural change but no significant difference has been observed in the real world. Wu et al. (2009) studied pedestrian crossing decisions at roundabouts, mainly evaluating pedestrian gap acceptance between moving vehicles in a virtual environment. Their results were consistent with real-world data. Bhagavathula et al. (2018) studied pedestrian crossing behaviour in virtual and real environments for different tasks. Their results showed no difference in most tasks except for the vehicle speed estimation and pedestrian's presence.

2.2. Pedestrian–AV interactions in virtual reality

Some VR studies have also specifically begun to study autonomous vehicle interactions with pedestrians. Wang et al. (2005) developed five different behaviours for an autonomous vehicle. The vehicle behaviour was successfully tested in different simulated traffic scenarios such as at intersections and for lane changing, in a simulated city and highway road networks. Keferböck and Riener (2015) studied autonomous vehicles interactions with pedestrians in a virtual environment. In one of their experiments, participants were asked to cross a road in front of them while a vehicle is approaching. Their experiment differs from ours in that the AV stops and shows (or not) a stop intent to pedestrians. This study aimed to show the importance of substituting communications between pedestrians and drivers by some explicit communication forms for self-driving cars. Pillai (2017) performed an experiment with participants on their crossing behaviour using virtual reality. They used task analysis to divide pedestrian–vehicle interaction as a sequence of actions giving two outcomes, either the vehicle passes first or the pedestrian crosses. Hartmann et al. (2017) proposed a testing procedure for studying safety critical systems, e.g. autonomous vehicles interacting with pedestrians, using VR techniques. This test bed can take into account different factors that could influence pedestrian behaviour such as their understanding of the environment, their body movement and their personality. Schmidt et al. (2019) investigated social cues in pedestrian–AV interactions in a VR environment. Their study showed that VR is a powerful tool for studying pedestrian–AV interactions but also that social cues could be manufactured through the vehicle trajectory. Stadler et al. (2019) validated the use of virtual reality for pedestrian–AV interactions. Moreover, their study showed that explicit HMI improves the interactions between autonomous vehicles and pedestrians. Deb et al. (2018) investigated pedestrian preferences for external features on a fully autonomous vehicle in VR. Their results showed a significant change in pedestrian crossing due to the external displays. Dey and Terken (2017) showed that facial communication cues such as eye contact do not play a major role in pedestrian crossing behaviour, and that the motion pattern and behaviour of vehicles are more important. The field study in Rothenbücher et al. (2016) showed similar results with an "unmanned" vehicle, suggesting that the same results could be found with autonomous vehicles. Risto et al. (2017) also showed that vehicle movement is sufficient for indicating the intention of drivers and presented some motion patterns of road users such as advancing, slowing early and stopping short. Chang et al. (2017) developed an AV prototype with "eyes" in a VR study. Their results showed that pedestrians were quicker at making their crossing decision and they feel safer knowing that the AV has seen them. Burns et al. (2019) studied pedestrian reactions (trust, safety) to different AV manoeuvres in a virtual environment. Their results showed that VR is realistic for studying pedestrian behaviour. Nuñez Velasco et al. (2018) studied pedestrian–vehicle interactions using recorded 360° videos displayed in VR. Their results showed that pedestrians may change their crossing behaviour based on an AV appearance. In Nuñez Velasco et al. (2019), the same authors studied pedestrian crossing behaviour in VR. Pedestrian trust levels were measured and they showed a higher crossing intention. No crossing difference was found between vehicle types. The authors used a mixed-model binomial logistic regression and found that the presence of a zebra crossing and large gaps between vehicles lead to more pedestrian crossing.

2.3. Game theory for pedestrian–AV interactions

Game theory has been widely used for various applications in transportation, such as vehicle to vehicle (V2V) communications Kim (2014); Talebpour et al. (2015); Tian et al. (2019), freight transportation Figliozzi et al. (2008), driver-AV interactions Flad et al. (2017); Na and Cole (2014). The few game theory models that focused on pedestrian–AV interactions are very recent. For example, Michieli and Badia (2018) proposed two variants of a game theory model for AV interactions with cyclists and pedestrians. Rahmati et al. (2020) developed a game theory model for pedestrian motion and walking behaviors. Rahmati and Talebpour (2018) then extended this model and built upon it a game theoretic framework for pedestrian–vehicle and pedestrian–pedestrian interactions. Li et al. (2018) proposed a level-k game theory model for autonomous vehicle controller at unsignalised intersections, based on a discrete time, set of actions and a reward function. The game theory model in this work called the sequential chicken model was proposed in Fox et al. (2018), it is based on the famous game of chicken. The model is detailed in Sec. 3.2.

*2.4. **Summary of the contributions***

The above related work has shown that virtual reality is a reliable tool for studying human behaviour. Despite these numerous studies, it finds no previous study with a game theoretic vehicle interacting with human pedestrians in a VR environment. The present study fills this gap and uses VR to run the game theoretic model proposed in Fox et al. (2018) on a virtual autonomous vehicle and then evaluates the behavioural preferences of human participants. Thus, this paper:

- shows the first attempt to quantitatively evaluate pedestrian behaviour during interaction scenarios with a game theoretic autonomous vehicle in a virtual reality environment;
- proposes a new method sufficient to infer specific numerical values for use in AV interaction control software;
- demonstrates the importance of VR for pedestrian behaviour study and for the development and testing of autonomous vehicle algorithms.

3. Methods

Our method consists in controlling an AV in VR using the game theory model, then measuring human subjects' behaviour during, and their responses after road crossing interactions with the AV under varied parameter settings of the game theory controller. In our previous work, we inferred game theory parameters to describe *human* behaviours, but here in contrast it is the parameters of the AV which are varied and studied. We seek the best parameters for the AV controller, which could for example then be built into real vehicles as part of their control.

Figure 2. VR Lab

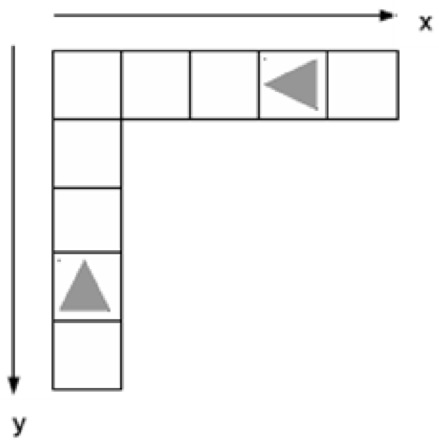

Figure 3. Sequential Chicken Model

3.1. VR Setup

The study was conducted using an HTC Vice Pro head mounted display (HMD). Participants did not use the HTC Vice controllers, as no interactions other than walking were required. The HMD was used with the HTC wireless adapter in order to facilitate easier movement during the simulation. We used an area of approximately 6 m by 3 m to conduct the simulation (as shown in Fig. 2), which was mapped using the usual HTC Vive room mapping system. The size of this area slightly exceeds that recommended by the manufacturer; however, we experienced no technical problem with tracking or system performance. The start position on the floor was marked with an “X” using floor tape, so that participants knew where to stand at the start of each simulation, prior to placing the HMD on their head. The simulation was created using the Unity 3D engine[2], and was run under Windows 10 on a PC based on an Intel Core i7-7700K CPU, with 32GB of RAM, and an Nvidia GeForce GTX 1080 GPU.

3.2. Game-theoretic AV behaviour model

The virtual AV was designed to drive using the sequential chicken model Fox et al. (2018). In this model, two agents (e.g., pedestrian and/or human or autonomous driver) called Y and X are moving towards each other at an unmarked intersection. This process occurs over a discrete space (the path is formed of squares) as in Fig. 3 and discrete times (‘turns’) during which the agents can adjust their discrete speeds. Here a turn corresponds to one discrete time step, i.e. the time offered to the agents to make a new decision. They simultaneously select their speed of either 1 square per turn (SLOW) or 2 squares per turn (FAST), at each turn. Space and time are discrete

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2 https://unity.com/

to keep the model simple and computationally tractable. Both agents want to pass the intersection as soon as possible to avoid travel delays, but if they collide, they are both bigger losers as they both receive a negative utility, U_{crash}. Otherwise if the players pass the intersection, each receives a time delay penalty, $-TU_{time}$, where T is the time from the start of the game and U_{time} represents the value of saving one turn of travel time.

The model assumes that the two players choose their actions (speeds) $a_Y, a_X \in \{1,2\}$ simultaneously then implement them simultaneously, at each of several discrete-time turns. There is no lateral motion (positioning within the lanes of the roads) or communication between the agents other than via their visible positions. The game is symmetric, as both players are assumed to know that they have the same utility functions (U_{crash}, U_{time}), hence they both have the same optimal strategies. These optimal strategies are derivable from game theory together with meta-strategy convergence, via recursion. Sequential chicken can be viewed as a sequence of one-shot sub-games, whose payoffs are the expected values of new games resulting from the actions, and are solvable by standard game theory.

The (discretised) locations of the players can be represented by (y,x,t) at turn t and their actions $a_Y, a_X \in \{1,2\}$ for speed selection. The new state at turn $t+1$ is given by $(y+a_Y, x+a_X, t+1)$. We define $v_{y,x,t} = (v^Y_{y,x,t}, v^X_{y,x,t})$ as the value (expected utility, assuming all players play optimally) of the game for state (y,x,t). As in standard game theory, the value of each 2×2 payoff matrix can then be written as,

$$v_{y,x,t} = v(\begin{bmatrix} v(y-1,x-1,t+1) & v(y-1,x-2,t+1) \\ v(y-2,x-1,t+1) & v(y-2,x-2,t+1) \end{bmatrix}), \tag{1}$$

which can be solved using dynamic programming assuming meta-strategy convergence equilibrium selection. Under some approximations based on the temporal gauge invariance described in Fox et al. (2018), we may remove the dependencies on the time t in our implementation so that only the locations (y,x) are required in computation of $v_{y,x}$ and optimal strategy selection.

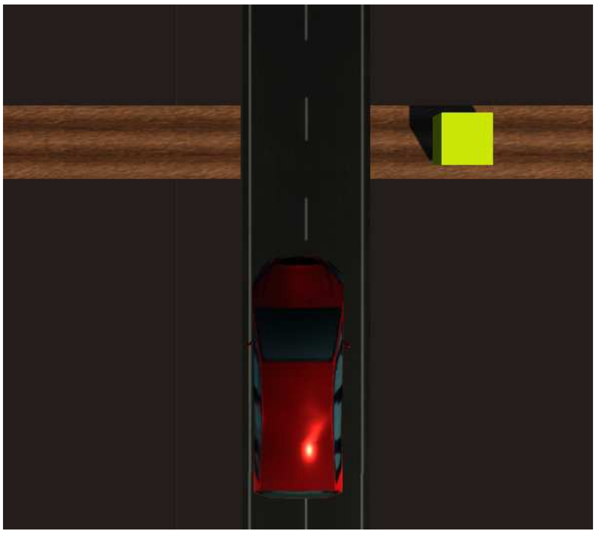
The virtual car model was imported from Unity Asset Store. The AV began driving 40 meters away from the intersection. The vehicle moved and adapted its behaviour to participants' motion. Every time step, the AV observed the current position of the pedestrian and made its decision based on the game theory model. The AV was designed not to stop completely for any pedestrian, rather it was designed only to slow to a lower but nonzero speed if necessary to yield to them. This was because a complete stop could potentially last forever, while ensuring a positive speed at all times guarantees a finite length interaction, which is required by the finite mathematics of the game theory model. In fact, in the sequential chicken model, if the two players play optimally, then there must exist a non-zero probability for a collision to occur. Intuitively, if we consider an AV to be one player that always yields, it will make no progress as the other player will always take advantage over it, hence there must be some threat of collision.

3.3. Human experiment

We invited members of staff and students from the University of Lincoln to take part in our study composed of three experiments, under the University of Lincoln Research Ethics. A few participants did the three experiments at different moments, some did two experiments and some others did only one experiment. Participants were not informed about the virtual vehicle behaviour, so they did not know that it was an autonomous vehicle nor that it had a game theoretic behaviour.

3.3.1. Experiment 1

We had 11 participants, 10 males and 1 female aged between 19 and 37 years old, who took part in this first experiment, seven of them had previous experience with VR. Participants were asked to cross a road in front of them as they would do in everyday life. They should stop moving on the other side of the road, when they reach a yellow cube used as a VR obstacle which people would avoid. The cube was located there for safety reasons, so the participants do not walk into a wall in real life, as shown in Fig. 2. A vehicle approaches from their right hand side. The AV's full speed was 30km/h, its lowest speed was 15km/h and it updated its decision every 0.02s. Participants began walking about 4 meters away from the intersection. Prior to the experiment, participants were

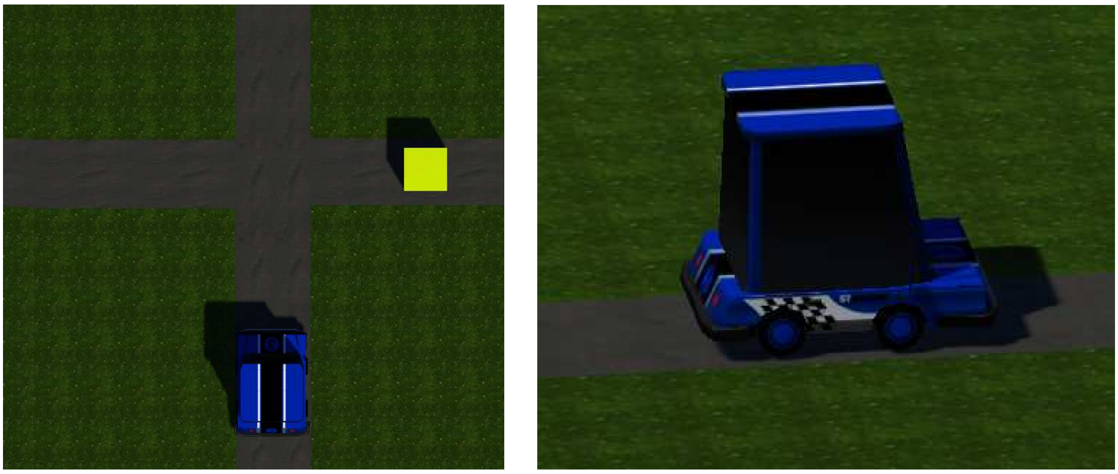


(a) Top view of the scene used for Experiments 1 and 2

(b) Virtual Autonomous Vehicle

(c) Participant taking part in the study

Figure 4. VR Experiment



(a) Top view of the scene **(b)** Small virtual vehicle

Figure 5. Experiment 3

introduced to the experimental setup and trained on walking within the VR environment with the VR headset. There were 6 trials per participants in the virtual environment with the first trials considered as practice runs in order to get the subjects comfortable with the setup before the actual data collection.

3.3.2. Experiment 2

Nine participants, 7 males and 2 females, aged from 21 to 39 years old took part in the study. Seven participants had previous experience with VR. Participants were given the same instructions as in Experiment 1, the environment and the AV's speed were also the same. The particularity here is that participants were asked, after each interaction, whether they preferred their last interaction with the vehicle or the previous one, in the sense of whether they found the vehicle behaviour more "natural" and more "realistic". Note that this is different from asking for a preference based on their own utility such as whether they managed to cross quickly. At each new interaction, the parameters were adjusted by the experimenter using a manual gradient descent, to seek parameters for the autonomous vehicle that were the most preferred by the participant. Two parameters were changed, the first one being about the spatial motion i.e. the number of discrete cells used in the sequential chicken model and the second parameter was about the time delay i.e. the amount of time that would elapse between two decisions made by the AV. There were 8 proposed parameters in the spatial axis {3 cells, 5 cells, 10 cells, 15 cells, 20 cells, 25 cells, 30 cells, 40 cells} and 3 proposed in the temporal axis {0.02s, 0.5s,1.0s}. The experimenter would ideally move one step along each axis per interaction, but the experimenter's subjective intuition was also allowed to hypothesize other parameter changes to try to speed up the gradient descent. This is an acceptable use of experimenter subjectivity because the aim of gradient descent is only to find the best parameters, so any form of proposal is acceptable if it gives better results than previous ones.

3.3.3. Experiment 3

This experiment investigated pedestrian interactions with a last-mile type delivery vehicle. The protocol was exactly the same as in Experiment 2, except that here, the environment was designed to look more like a park or a garden, by replacing the wide tarmac road with a narrower pathway without markings as shown in Fig. 5a. This was to test whether this type of environment alters pedestrian behaviour. The type of vehicle used was also different, it was smaller, with a different colour and looked like a single person podcar, as shown in Fig. 5b, and for this reason, the AV's lowest speed was set to 4km/h, to show a significant deceleration. The 3D car model was imported from Unity Asset Store. Six participants, 5 males and 1 female, aged from 21 to 39 years old took part in the study, with 5 participants having had previous experience with VR.

3.4. Gaussian process parameter posterior analysis

We used Gaussian process (GP) regression Rasmussen and Williams (2005) to fit the posterior belief over the behavioural parameters of interest, $\theta = (U_{crash}, U_{time})$ from the observed data, D. Under the sequential chicken model, M, these are,

$$P(\theta|M,D) = \frac{P(D|\theta,M)P(\theta|M)}{\sum_{\theta'} P(D|\theta',M)P(\theta'|M)}. \tag{2}$$

We assume a flat prior over θ so that,

$$P(\theta|M,D) \propto P(D|\theta,M), \tag{3}$$

which is the data likelihood, given by,

$$P(D|\theta,M) = \prod_{game} \prod_{turn} P(d_X^{game,turn}|y,x,\theta,M'), \tag{4}$$

where $d_{player}^{game,turn}$ are the observed action choices, and y and x are the observed player locations at each *turn* of each *game*. Here M' is a noisy version of the optimal sequential chicken model M, which plays actions from M with probability $(1-s)$ and maximum entropy random actions (0.5 probability of each speed) with probability s. This modification is necessary to allow the model to fit data where human players have made deviations from optimal strategies which would otherwise occur in the data with probability zero. Real humans are unlikely to be perfectly optimal at any time as they may make mistakes of perception and decision making. This is a common method to weaken psychological models to allow non-zero probabilities for such mistakes if present Camara et al. (2018a,b); Lu et al. (2016).

For a given value of θ, we may compute the optimal strategy for the game by dynamic programming as shown in Algorithm 1. Optimal strategies are in general probabilistic, and prescribe the $P(d_X^{game,turn}|y,x,\theta,M)$ terms to compute the above data likelihood. We then use a Gaussian process with a Radial Basis Function (RBF) kernel to smooth the likelihood function over all values of θ beyond a sample whose values are computed explicitly. In practice, this is performed in the log domain to avoid numerical computation problems with small probabilities. The resulting Gaussian process is then read as the (un-normalized, log) posterior belief over the behavioural parameters $\theta = \{U_{time}, U_{crash}\}$ of interest.

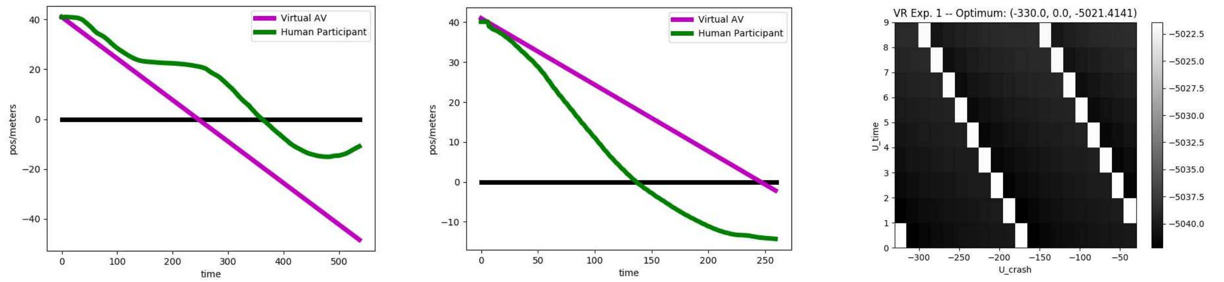
To fit parameters of the discrete sequential chicken model to the continuous pedestrian trajectory data, it was discretised assuming an average speed of 1m/s and sampled every 3 time steps; a similar approach was used in Camara et al. (2020c).

Algorithm 1 Optimal solution computation

for U_{crash} in range($U_{crash_{min}}$, $U_{crash_{max}}$) **do**
    for U_{time} in range($U_{time_{min}}$, $U_{time_{max}}$) **do**
        S $\leftarrow$ strategy matrix$(NY \times NX \times 2)$ for $P($player X chooses speed $2|y,x)$
        loglik = 0
        for each game in data **do**
            for each turn in game **do**
$$\text{loglik} = \prod_{game} \prod_{turn} (1-s)P(d_X^{game,turn}|y,x,\theta,M) + s(\frac{1}{2})$$
            end for
        end for
        Store loglik(U_{crash}, U_{time})
    end for
end for
maxloglik $\leftarrow$ max of loglik(U_{crash}, U_{time})

Table 1. Statistics about pedestrian crossing choices

Pedestrian Action	Experiment 1	Experiment 2	Experiment 3
Crossing	6	12	30
Stopping	49	118	58
Total	55	130	88



(a) Pedestrian–AV trajectories: stopping **(b)** Pedestrian–AV trajectories: crossing **(c)** Pedestrian behavioural preference

Figure 6. Results Experiment 1

4. Results

4.1. Statistics

Table 1 shows some statistics about pedestrian crossing choices in the three experiments. We observe that very few pedestrians decided to cross in Experiments 1 and 2, about 10% crossings in each, whereas in Experiment 3, participants were more assertive and crossed in 34% of the interactions. This result is not surprising, in fact, this can be easily explained by the difference in the AV's slow speed, 15km/h (Experiments 1and 2) versus 4km/h (Experiment 3), showing that pedestrians adapt their behaviour to the vehicle's behaviour rather than on its appearance, as found in Dey and Terken (2017); Risto et al. (2017).

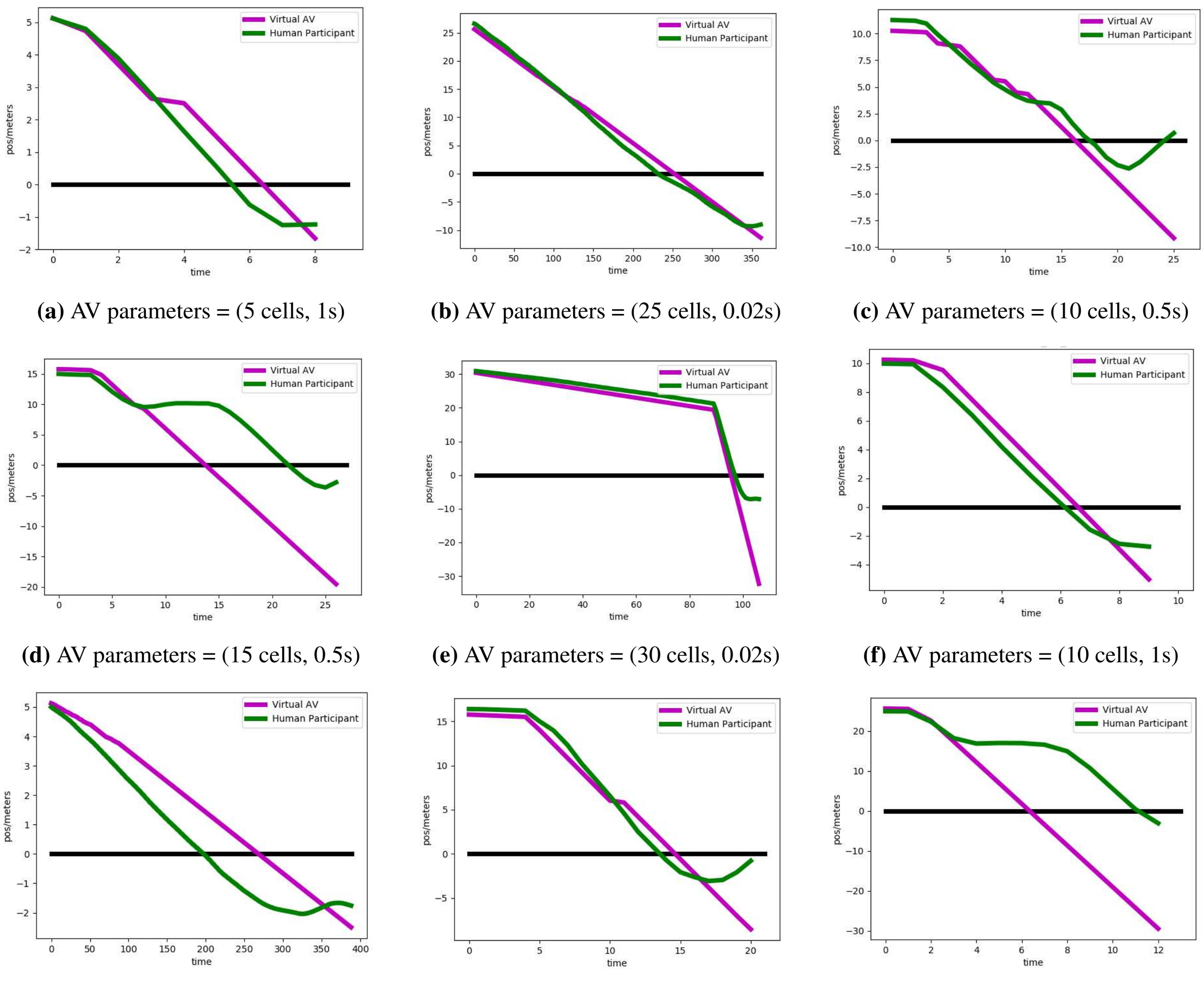
4.2. Pedestrian behaviour in Experiment 1

In total, 55 pedestrian–vehicle interactions were recorded. Among those interactions, pedestrians managed to cross the road before the AV reached the intersection only 6 times. These crossings usually happened after the first trials, by pedestrians who felt more confident after evaluating/gauging the AV driving style. Most interactions looked similar to Figs. 6a (pedestrian stopping) and 6b (pedestrian crossing), which show the trajectories of the human participant and the virtual autonomous vehicle. In particular, the trajectory profile in Fig. 6a shows that pedestrians were slowing down very quickly after seeing the AV, they were not playing optimally the game of chicken, so that the AV could cross most of the time.

Using Algorithm 1 for Experiment 1 trajectories, we obtain a behavioural parameter $\theta = U_{crash}/U_T = -330/0$, for participants, as shown in Fig. 6c. This reveals that pedestrians valued the avoidance of a crash 330 times more than a 0.02s time saving per turn, resulting in pedestrians being less assertive in crossing the road. In comparison, previous laboratory experiments found that participants valued time saving more than collision avoidance Camara et al. (2018a,b). Thus, the use of virtual reality has made the interactions much more realistic.

4.3. Pedestrians' evaluation of the virtual AV behaviour using gradient descent (Experiments 2 and 3)

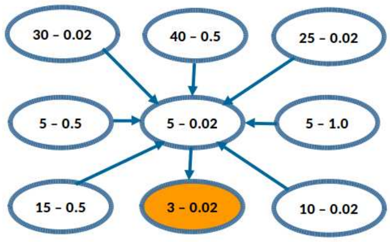
Fig. 7 shows examples of pedestrian–AV trajectories from Experiments 2 and 3. Examples are presented in Fig. 8 from four participants' interactions with the virtual AV for finding their most preferred AV parameters using the gradient descent approach. The results for pedestrians' most preferred parameters are summarized in Fi.g. 9a for Experiment 2 and in Fig. 9b for Experiment 3. The mean parameter values for the experiments



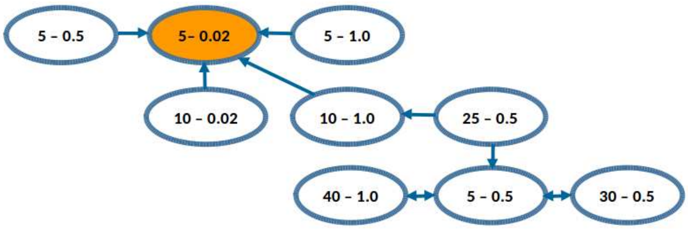
(a) AV parameters = (5 cells, 1s)
(b) AV parameters = (25 cells, 0.02s)
(c) AV parameters = (10 cells, 0.5s)
(d) AV parameters = (15 cells, 0.5s)
(e) AV parameters = (30 cells, 0.02s)
(f) AV parameters = (10 cells, 1s)
(g) AV parameters = (5 cells, 0.02s)
(h) AV parameters = (15 cells, 0.5s)
(i) AV parameters = (25 cells, 1s)

Figure 7. Examples of pedestrian–AV trajectories from Experiments 2 and 3

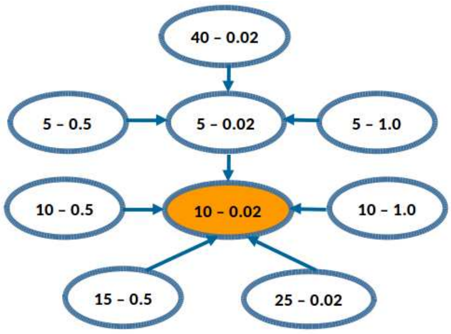
{mean_exp2 = (16 cells, 0.34s), mean_exp3 = (19 cells, 0.35s)}, are found to be quite similar. That suggests that pedestrians had similar preferences for the AV behaviour in both environments but also that they behaved in the same way.



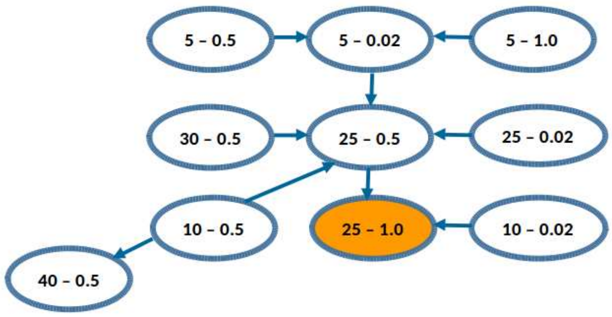
(a) Preferred AV parameters = (3 cells, 0.02s)



(b) Preferred AV parameters = (5 cells, 0.02s)

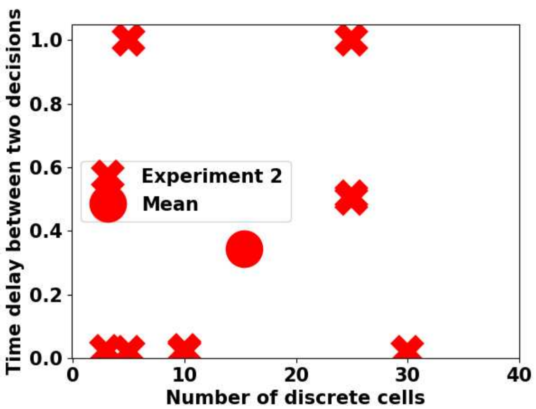


(c) Preferred AV parameters = (10 cells, 0.02s)

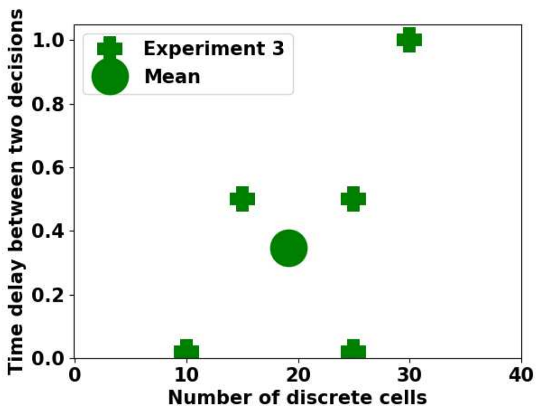


(d) Preferred AV parameters = (25 cells, 1s)

Figure 8. Examples of gradient descent approach for pedestrian most preferred AV parameters selection



(a) Experiment 2

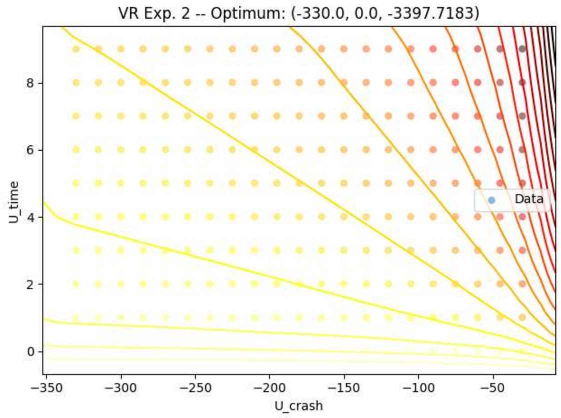


(b) Experiment 3

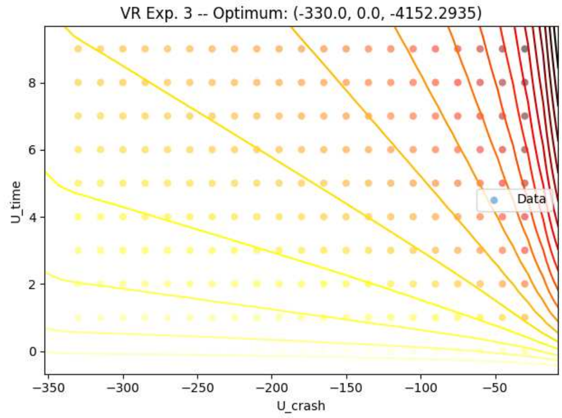
Figure 9. Results of pedestrian most preferred AV parameters using gradient descent

4.4. Evaluation of pedestrian crossing behaviour using Gaussian process regression (Experiments 2 and 3)

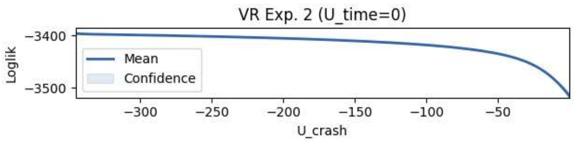
After applying Gaussian process regression and optimising s to maximise the likelihood at the Maximum A Posteriori (MAP) point of θ, the posterior distribution over $\theta = \{U_{crash}, U_{time}\}$ are shown in Figs. 10a and 10b. The MAP estimate of the parameters is found to be the same for Experiments 2 and 3, it is around $U_{crash} = -330$, $U_{time} = 0$, at $s_2 = 0.32$, and $s_3 = 0.2057$, respectively. Unsurprisingly, the same parameter estimate was found in Experiment 1. The 330 : 0 ratio in the utilities means that assuming the noisy model M' the subjects valued the avoidance of a crash 330 times than saving any time. And the s_i value ,$i \in \{2,3\}$, means that the subjects



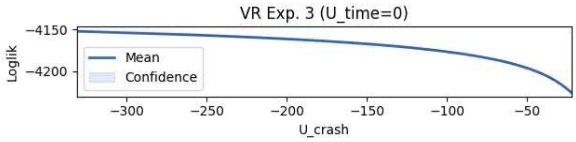
(a) Gaussian process regression for Experiment 2



(b) Gaussian process regression for Experiment 3



(c) GP slice for Experiment 2



(d) GP slice for Experiment 3

Figure 10. Pedestrian behavioural preferences for Experiments 2 and 3: Figs. 10a and 10b show the Gaussian process log-posterior over behavioural parameters. Figs. 10c and 10d show the slices through the Gaussian process showing standard deviation log-posterior confidence.

make mistakes from optimal behaviour in 32% and 20.57% of actions in Experiments 2 and 3, respectively. Significance of the results can be seen by inspection of the thin standard deviation widths of 1D slices through the 2D posterior as shown in Figs. 10c and 10d. The finding of the same MAP estimate for both experiments shows that participants behaved similarly within the two environments and with the different car models.

5. Discussion

The results provide new estimates for specific numerical parameters which AV controller software could use in the sequential chicken model to control interactions with pedestrians.

The result in study 1 is important as it shows that virtual reality makes pedestrian crossing behaviour more realistic than in the previous laboratory experiments Camara et al. (2018a,b). Pedestrians had a higher preference for avoiding collisions in VR, which gives confidence that the VR environment is more realistic than the previous laboratory experiments and therefore that the numerical parameters found next are good.

The other two experiments then showed that when interacting with an autonomous vehicle, pedestrians care more about the vehicle behaviour than its appearance, i.e. whether it should slow down, keep driving or completely stop for them, as found with the gradient descent method and in Dey and Terken (2017); Risto et al. (2017); Rothenbücher et al. (2016). An interesting point to raise here is that the gradient descent method provided numerical results that could be inserted into future experiments or even practical vehicles.

The results from the Gaussian process regression also showed that participants behave similarly in different environments and with different car models, similar to the results in Nuñez Velasco et al. (2019). In particular, in Experiment 3, it appeared that the smaller car and the park environment did not make much difference in pedestrian crossing behaviour. These VR studies also confirm that pedestrian behaviour can be represented by one parameter θ and that there is a linear mapping between U_{crash} and U_{time}, a similar result was found in Camara et al. (2018a,b).

There are some limitations with these experiments. The gradient descent takes a long time to run and it was hard for the experimenter to hypothesise which direction to follow, because after several interactions, participants sometimes rejected a set of preferred parameters that they approved several times before. It was also confusing and confounding to infer parameters for both pedestrians' own behaviour and their preferred AV behaviour.

Hence, other methods of learning the best behavioural parameters for the autonomous vehicle will be explored in future studies. At first, we plan to simplify the protocol by replacing the virtual game theoretic AV by a human participant driving a virtual vehicle, so that to learn the behavioural parameters of participant drivers and used them for the game theoretic AV. Future work will also further investigate pedestrian crossing behaviour with different car models and within different environments with a larger number of participants.

The GP results from a previous laboratory experiment showed that $U_{time} = 45$ was bigger than $U_{crash} = -30$ Camara et al. (2018a), which is unrealistic, here instead we obtain an absolute measure of $U_{crash} = -330$ that is much bigger than $U_{time} = 0$, meaning that participants valued collision avoidance much more than saving time. However, the statistics may not be powerful enough to distinguish between values of $U_{crash} \to -\inf$ and $U_{crash} =$ -330, this is shown in Figs. 10c and 10d with the curve becoming more and more horizontal for $U_{crash} < -300$. We believe that collecting larger data would help make the distinction and measure the parameters more accurately.

The results of these experiments should be consistent if moved from the VR lab to the real world (UK), because subjects were asked to behave as in real life and they are not incentivised to do otherwise. However, moving from one country to another, the numbers may vary because of different cultural norms Lee et al. (2020). The statistically implied values of travel times and human lives, and risk appetites, are well-known to vary between cultures and the sequential chicken analysis might help to better model and understand these relationships from data in the future.

Previous work Fricker and Zhang (2019) has shown that pedestrian–driver interactions at semi-crosswalks are different when the road changes from one way to a two-way street. For instance, it was observed that drivers tend to decelerate or stop more on the two-way setting. Thus, future work should investigate the effects of road settings on pedestrian–AV interactions.

Potential policy implications of this work include better understanding and regulating autonomous vehicle interactions with pedestrians. The sequential chicken model shows that unless AVs are able to inflict some kind of negative utility onto pedestrians, then pedestrians can always push in front of them to win interactions and impede the AV's progress. A collision is an obvious but extreme form of negative utility which policy obviously wishes to avoid. By understanding and quantifying how the tradeoff between time saved and risk of collision works, as in the present study, the game theory mathematics could then be used to replace the rare but extreme risk of collision with some other, more common but less extreme negative utility. One possible solution, proposed in Camara and Fox (2020), is to use humans' sense of psychological discomfort when their personal space is invaded by other agents (proxemics) as such a negative utility. Without this replacement, policy would either have to tolerate occasional actual, deliberate collisions by AVs, or risk them making no progress. With the replacement, AVs can operate safely and efficiently but within existing regulations which prevent collisions.

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