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Safety or efficiency? Estimating crossing motivations of intoxicated pedestrians by leveraging the inverse reinforcement learning

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ABSTRACT

Background: Intoxicated pedestrians are particularly vulnerable while crossing roads because of their impaired cognitive and decision-making abilities. A deeper understanding of the crossing behaviors of pedestrians under the influence serves as the foundations for formulation of tailor-made countermeasures.

Methods: In this study an experiment based on the immersive virtual reality was conducted, by which 53 samples of Hong Kong pedestrians' crossing trajectories before and after alcohol intake were collected. The K-means algorithm was first used to classify pedestrians into two distinct types, namely the risky and cautious, according to the post-encroachment time during all street crossings. The cutting-edging inverse reinforcement learning was then harnessed to uncover the safety and efficiency motivations underlying crossing behaviors impacted by alcohol. The results were validated by comparing the observed behaviors with those generated by reinforcement learning.

Results: Our results revealed substantial differences in safety and efficiency motivations between the two types of pedestrians. Notably, the cautious type emphasized safety more than the risky. Under the influence of alcohol, both types of pedestrians exhibited a shift in motivations from safety to efficiency. In addition, road markings hardly influenced pedestrian crossing motivations, whereas traffic directions significantly altered the motivations of cautious pedestrians under sober conditions.

Conclusions: Our study sheds more lights on unobserved motivations guiding crossing behaviors of pedestrians under the influence. The inverse reinforcement learning is proven promising in imitating complex pedestrian crossing behaviors under a quantifiable, reliable manner.

Keywords: Drunk pedestrians; crossing behaviors; pedestrian–motor vehicle interactions; virtual reality; inverse reinforcement learning

1. Introduction

Walking is an essential travel mode suitable for everyone. However, owing to their lack of protective systems, pedestrians are highly susceptible to road accidents, accounting for 23% of all road fatalities and resulting in approximately 310,500 deaths annually, leading to substantial psychological, socioeconomic, and health burdens (WHO, 2023). Alcohol has long been acknowledged as a contributing factor for road trauma. For example, in 2021 alcohol involvement was reported in 49% of fatal pedestrian crashes in the United States (NHTSA, 2023). While driving under the influence has garnered significant research attention and led to the enactment of stringent legislation to combat drunk driving, there have been relatively few studies specifically examining the impact of alcohol consumption on walking behaviors (Oviedo-Trespalacios et al., 2021).

In fact, alcohol-impaired pedestrians experience diminished cognitive functioning, which adversely affects their decision-making abilities (Eichelberger et al., 2018). They also face a higher risk of fatalities and severe injuries than sober pedestrians when involved in traffic accidents (Öström and Eriksson, 2001; Dultz and Frangos, 2013). Statistics show that in the United States, approximately 30% of pedestrian fatalities had a blood alcohol concentration (BAC) of 0.08 g/dL or higher (NHTSA, 2023), while alcohol was involved in 58% and 48% of traffic fatalities among pedestrians in South Africa and the United Kingdom, respectively. Research also confirms that intoxicated pedestrians are more likely to engage in unsafe behaviors such as sitting or lying on the road (Hutchinson et al., 2010), jaywalking, and failing to select safe gaps when crossing (Oxley et al., 2006). To date, most studies have utilized available traffic injury data to estimate the burdens faced by alcohol-impaired pedestrians (Lee and Abdel-Aty, 2005; Dultz et al., 2011) or conducted questionnaire surveys to explore the intention of walking under the influence (Haque et al., 2012; McGhie et al., 2012; Gannon et al., 2014; Oviedo-Trespalacios et al., 2021). Given the limited research on intoxicated pedestrians' behaviors using real trajectory data, further investigation into the influence of alcohol on pedestrian decision-making processes is warranted.

Motivation is the driving force behind human actions, initiating, guiding, and executing goal-oriented behaviors (Nevid, 2012). Pedestrian behaviors are propelled by underlying motivations aimed at maximizing specific satisfaction and objectives, and sometimes, they are even unknown to pedestrians themselves and unobservable directly (de Araújo, 2012). The prevalence of risky pedestrian behaviors significantly contributes to traffic accidents, highlighting the critical need for elucidating pedestrian behaviors, particularly the motivations that underline such behaviors. Numerous studies have explored the role of safety perception in pedestrian crossing behavior, considering contextual factors such as the perceived speed and distance of oncoming vehicles, as well as other environmental conditions (Sisiopiku and Akin, 2003; Catillo et al., 2015; Mukherjee and Mitra, 2019). Although perceptual states can influence behavior, they are typically not considered motivational in nature, because perception reveals the current state of affairs but does not dictate what actions to take (McClelland and Jorba, 2023). Some individuals may be motivated by efficiency, aiming to cross the road as quickly as possible to reach their destination. In contrast, others might prioritize safety, opting to wait longer to minimize the risk of an accident. Pedestrian motivations could potentially influence their perceptions (Balcetis and Dunning, 2006). For example, a person with a strong motivation for efficiency might perceive a situation as safe for crossing, even if it might not be. However, only a limited number of studies have investigated pedestrian motivations (Yagil, 2000; Guinn and Stangl, 2014; Soathong et al., 2021), and even fewer have explored the motivations of pedestrians under the influence of alcohol. Regarding research designs, most studies employed questionnaire surveys to collect pedestrians' responses under hypothetical scenarios and utilized statistical methods to model unobserved pedestrian motivations according to psychological theories. While such an approach offers significant advantages in modeling unobserved attitudes, subjective norms, and perceived behavioral control by adjusting for a wide diversity of contributing factors, it has several inherent limitations (Train and Wilson, 2008):

- Non-response bias may exist inevitably, as differences in various factors may occur between individuals who choose to respond and those who do not.
- Participants' responses are highly subjective and can be influenced by various factors (e.g., question misinterpretation, memory gaps, and boredom), making it challenging to collect subjective information about complicated human behaviors without bias.
- Defining a comprehensive range of questions and accurately estimating pedestrian motivations appear to be intractable due to their unobservable nature. Additionally, collecting quantitative data to directly estimate motivations is challenging.

To address these challenges existing in the subjective estimations, the emerging inverse reinforcement learning (IRL) method has the potential of estimating the motivations underlying pedestrian crossing behaviors. Unlike the reinforcement learning (RL) approach which necessitates a manually designed reward function to train an agent for optimal solutions, IRL can autonomously learn the reward function from a set of expert demonstrations, thus emulating expert behaviors (Gleave and Toyer, 2022). This technique has been successfully applied in transportation research, e.g., travel demand management (Liu et al., 2022), decision-making for autonomous vehicles (Schwarting, 2018), vehicular trajectory prediction (Geng et al., 2023), and modeling of driving behaviors (Bhattacharyya et al., 2022), pedestrian behaviors (Nasernejad et al., 2021), and pedestrian–cyclist interactions (Alsaleh and Sayed, 2020).

Pedestrian crossing behavior entails a trade-off between safety and efficiency, as pedestrians must choose between crossing swiftly to save time and patiently waiting for safety (Zhu et al., 2021; 2023). For instance, a study conducted in India observed that pedestrians selected crossing locations that offered convenience to minimize delays (Chandra et al., 2014). Our study therefore focuses on elucidating crossing motivations of pedestrians under the influence by leveraging IRL instead of solely predicting or recovering individual behaviors. A virtual reality (VR) based experiment involving intoxicated pedestrians in diverse traffic environments is conducted to capture the real behaviors (Ye et al., 2023). Pedestrians are categorized into two types, namely risky and cautious types, according to their post-encroachment time (PET) during all VR street crossings. This classification allows for investigating the effect of alcohol on pedestrian motivations. By extracting the reward function from authentic pedestrian behavior demonstrations within the VR environment, we can objectively estimate pedestrian motivations in a quantifiable manner.

The remainder of this paper is organized as follows. Section 2 reviews the literature on drunk pedestrian behaviors, motivations, and IRL. Section 3 provides details of the data collection process and proposes IRL methods. Section 4 presents and interprets the experimental results. Section 5 discusses the findings and limitations of the study. Finally, Section 6 draws conclusions.

2. Literature Review

2.1 Studies on alcohol-impaired pedestrian behaviors

There is an increasing focus on the issue of drunk walking, and substantial evidence has highlighted the elevated risk of pedestrian injuries associated with alcohol consumption. Studies have predominantly relied on aggregated hospital admission or police-reported traffic accident data to assess the impact of alcohol on pedestrian injuries. Dultz et al. (2011) revealed that individuals with alcohol involvement exhibited significantly higher injury severity scores, along with a higher incidence of injuries to the head, neck, face, chest, abdomen, extremities, and pelvic girdle. Hezaveh and Cherry (2018) investigated crash characteristics involving pedestrians under the influence and revealed a positive correlation between injury severity and the prevalence of alcohol-related pedestrian crashes. Pawlowski et al. (2019) revealed a predominance of male fatalities, with nearly half of the victims were under the influence of alcohol. These results align with the findings of other studies (Kemnitzer et al., 2019). Furthermore, the spatial patterns of alcohol consumption and pedestrian injuries have been investigated. Nesoff et al. (2018) employed a negative binomial regression to examine the relationship between the number of alcohol outlets and pedestrian injury rates. Their study revealed a significant correlation between off-premises alcohol outlets and the frequency of pedestrian injuries.

Given the detrimental impact of alcohol on pedestrian safety, researchers have also explored the effectiveness of traffic laws and countermeasures in mitigating drunk walking-related injuries. Živković et al. (2016) conducted a retrospective autopsy study in Belgrade, Serbia from 2006 to 2012, which compared pedestrian fatalities under the old traffic safety law (2006-2009) and the new law (2010-2012). While the total number of pedestrian fatalities decreased significantly in the new law period, the proportions of pedestrians testing positive for alcohol and severely intoxicated pedestrians remained consistent. These results indicate a limited impact of the new traffic law in addressing accidents involving drunk pedestrians. Similarly, Eichelberger et al. (2018) analyzed data of United States from 1982 to 2014, which found a 19% reduction in high BAC levels among fatally injured passenger vehicle drivers, but only a 10% and 7% decrease among pedestrians and bicyclists, respectively. These findings imply that many countermeasures employed to combat alcohol-impaired driving may have weak effectiveness in reducing fatalities among alcohol-impaired pedestrians and bicyclists.

Although several studies have focused on the macroscopic effects of alcohol on pedestrian injuries, studies on the specific effects of alcohol on microscopic pedestrian behaviors are scarce. Oxley et al. (2006) experimentally assessed the gap selection behaviors of both intoxicated and sober pedestrians. Regarding physiological impairment, no significant differences were observed between groups in walking time. However, in terms of psychological responses, the decision-making time for sober adults (mean = 1.46 s, standard error = 0.02 s) was significantly lower than those observed for the high BAC alcohol group (mean =

1.63 s, standard error = 0.03 s) and notably shorter than those of the low BAC alcohol (mean = 1.86 s, standard error = 0.06 s). Furthermore, at a distance gap of 22 m, approximately 10% of the high BAC alcohol group indicated that they would have crossed within the very small time gap of 1 s, whereas almost no pedestrians from the low BAC and sober groups chose to cross. It can be found that highly intoxicated pedestrians exhibited a lack of awareness regarding their impairment, a propensity for risky road crossings, and difficulties in promptly integrating speed and distance information to select safe gaps. Furthermore, intoxicated pedestrians were found to be less likely to cross the street at designated crosswalks with signals and more likely to either cross against the signal or engage in jaywalking (Dultz et al., 2011). Moreover, studies have investigated the influence of conformity and group identity on drunk walking intentions, revealing that the presence of friends was associated with the highest levels of drunk walking intentions (McGhie et al., 2012). In VR-based crossing experiments, intoxication has been observed to impair perceptual motor responses, particularly among young adults (Ye et al., 2023). Unlike Ye et al. (2023) who used traditional statistical approaches to model the crossing behaviors of intoxicated pedestrians under unfamiliar driving rules, the present study aims to reveal the safety and efficiency motivations underlying pedestrian crossing behaviors under the influence of alcohol.

To the best of our knowledge, studies of the influence of alcohol on the underlying motivations driving pedestrian behaviors are scarce. This knowledge gap is significant, as it is crucial to elucidate the mechanisms behind drunk pedestrian behaviors and the potential factors contributing to their involvement in traffic crashes. Investigating the effect of alcohol on pedestrian motivations gains insights into developing effective countermeasures for mitigating alcohol-related pedestrian crashes. Therefore, our study clarifies pedestrian motivations during mid-block crossings, both in the presence and absence of alcohol influence.

2.2 Pedestrian motivations

Motivation is widely explored across various disciplines, including psychology, education, and organizational behavior. In psychology, several cognitive theories of motivation have been developed, focusing on how active processing and interpretation of information drive behavior. Several theories have gained widespread acceptance, e.g., expectancy–value theory (Wigfield et al., 2009), the attribution theory of motivation (Weiner, 1972), self-determination theory (Deci and Ryan, 2012), self-efficacy theory (Bandura and Adams, 1977), and achievement goal theory (Senko et al., 2011). These theories help to untangle the complex mechanisms underlying human motivations and gain insights into the factors that shape individual choices and actions.

Researchers in the field of transportation have studied pedestrian motivations according to the principles of various motivation theories. Yagil (2000) conducted a questionnaire study involving 205 students to explore the instrumental (external factors) and normative (internalization of laws) motivations that influenced the students' adherence to safety rules while crossing, which revealed that violation behaviors could be predicted by perceived consequences and normative motives. Similarly, Guinn and Stangl (2014) employed a questionnaire survey method to investigate the motivations of pedestrians and bicyclists influenced by physical and perceptual factors, which highlighted the significance of the opportunity to exercise as a factor influencing the decision to walk or ride a bike. Soathong et al. (2021) utilized an on-site questionnaire survey to explore the motivational factors associated with pedestrians' risky crossing behaviors at mid-blocks. The results of factor analysis and structural equation modeling indicated that crossing intention was driven by habit and attitude, revealing a willingness to take risks to save travel time and reduce walking distances.

In the realm of pedestrian crossing behavior studies, econometric methods have gained widespread adoption due to their ability to unravel the relationship between influential factors and crossing behaviors. Discrete choice models have been predominantly utilized when dealing with discrete response variables such as crossing intention or the intention to walk under the influence. These models include the binary logit model (Velasco et al., 2019), multinomial logit model (Tezcan et al., 2019), mixed logit model (Velasco et al., 2019), and regret-based panel mixed multinomial logit model (Zhu et al., 2021; 2023), among others. For continuous response variables such as waiting time, reaction time, crossing speed, distance gap from the approaching vehicle, and perceived safety, linear regression models like the multiple linear model (Zhuang and Wu, 2011; Shaaban et al., 2018), linear mixed model (Luu et al., 2022; Kwon et al., 2022; Ye et al., 2023), and generalized linear mixed model (Aghabayk et al., 2021) have been employed. Recent studies have also introduced game theoretical approaches to model pedestrian–vehicle interactions at intersections, with the aim of explaining factors that influence the decisions made by motorists and pedestrians jointly (Zhang and Fricker, 2021; Zhu et al., 2022; Li et al., 2023). While these methods show promise in modeling observable pedestrian crossing behaviors, additional efforts are needed to capture the motivations behind crossing behaviors that cannot be directly observed.

Given the unobservable nature of pedestrian motivation, stated preference questionnaire surveys have emerged as a prominent method for collecting and measuring subjective motivation information regarding pedestrian behaviors. However, this method suffers inherently from several limitations, such as the social desirability bias, hypothetical bias, sample bias, misunderstanding, lack of realism, and limited behavior validity. To address these challenges, one potential solution is to harness the reinforcement learning (RL) to simulate the crossing behaviors of alcohol-impaired pedestrians and unveil the underlying mechanism by capturing the interaction between the agents and the environment. Built on the Markov decision process (MDP), the RL involves training an agent to select the optimal policy that maximizes its expected total rewards for a given task. The reward function, despite being unavailable, unobservable, and intricate in real-world applications, needs to be preset based on the domain knowledge. Such practice is very likely to induce arbitrariness and mismatch. Fortunately, the IRL has been proposed to reason what the agents attempt to achieve (Ng and Russell, 2000).

2.3 Inverse Reinforcement Learning

As a nonparametric and model-free approach, the IRL does not rely on manual specification of the reward function and can deduce the preference of agents by observing the expert's demonstration. Several IRL-based algorithms have been proposed to recover the reward function, such as the feature matching IRL (Abbeel and Ng, 2004), Bayesian IRL (Ramachandran and Amir, 2007), MaxEnt IRL (Ziebart et al., 2008; Ziebart, 2010), and Gaussian process IRL (Levine et al., 2011). Upon obtaining the reward function, RL can be used to derive the optimal policy and train agents to maximize the total rewards. By comparing the behaviors of the agents with the observed (Alsaleh and Sayed, 2020; Liu et al., 2022), we can determine whether the reward function estimated by the IRL adequately characterizes the motivations behind the actions.

Typically, the IRL technique is suited to two main applications. One is to replicate the behavior of experts. This is particularly relevant for tasks characterized by complex, dynamic, and difficult-to-define features. The objective is to establish optimal policies that adapt to environmental changes and are suitable for agent-based microsimulation or prediction tasks. For example, Nasernejad et al. (2021) employed the Gaussian process IRL to reproduce pedestrian evasive actions in pedestrian–vehicle conflict situations. Geng et al. (2023) proposed a framework that integrated the IRL and risk aversion modules for multimodal vehicular trajectory prediction at urban unsignalized intersections. Their results demonstrate the reliability of the IRL in generating trajectories that mimic sequential decision-making process of human drivers.

Another purpose is to elucidate the underlying reward (utility) function and explain the motivations of optimally behaving agents. Alsaleh and Sayed (2020) used the MaxEnt IRL and feature matching IRL algorithms to model pedestrian–cyclist interactions based on the real trajectory data extracted through computer-vision algorithms. The recovered reward function successfully inferred cyclist preferences during their interactions with pedestrians in shared spaces. Similarly, Liu et al. (2022) leveraged the feature matching IRL to capture travelers' preferences for departure times based on the virtual experiment data. By solving the weights of the reward function, the departure time choice behaviors could be imitated and the impact of different incentive profiles on departure time choices could be assessed accordingly.

However, limited studies have employed IRL method in the field of traffic safety, especially for behavior understanding and analysis. In this study, the second purpose of IRL was preferred, as the research focuses on elucidating the safety and efficiency motivations behind pedestrian crossing behaviors under the influence of alcohol, rather than trajectory prediction. This study represents the first instance of utilizing IRL to estimate pedestrian motivations with and without the effect of alcohol during mid-block crossing tasks.

3. Methodology

This study analyzed experimental data derived from VR pedestrian crossing scenarios, encompassing both situations before and after alcohol consumption. First, a clustering algorithm was used to classify pedestrians according to their crossing behaviors. Then, the IRL algorithm was used to extract the underlying reward functions that drive pedestrian crossing motivations for each identified group. These reward functions were then used to model pedestrian crossing behaviors. The RL algorithm was applied to train agents using the recovered reward functions to validate the IRL results' effectiveness. The behaviors of these trained agents were observed and compared with those of pedestrians. The overall framework of the methodology is illustrated in Fig. 1.

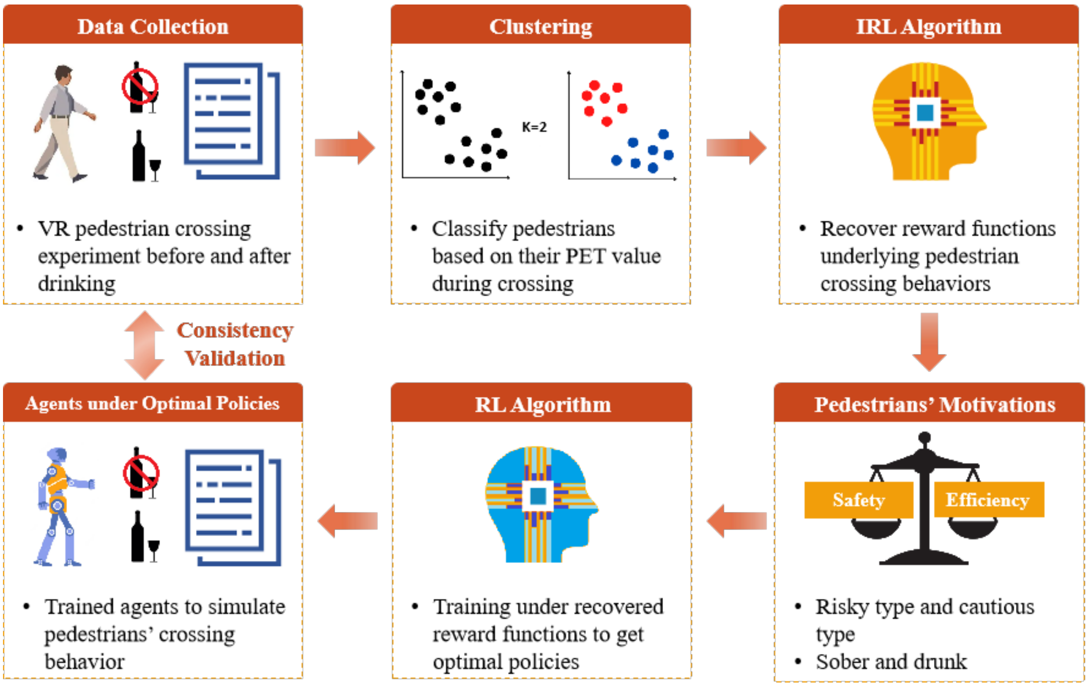
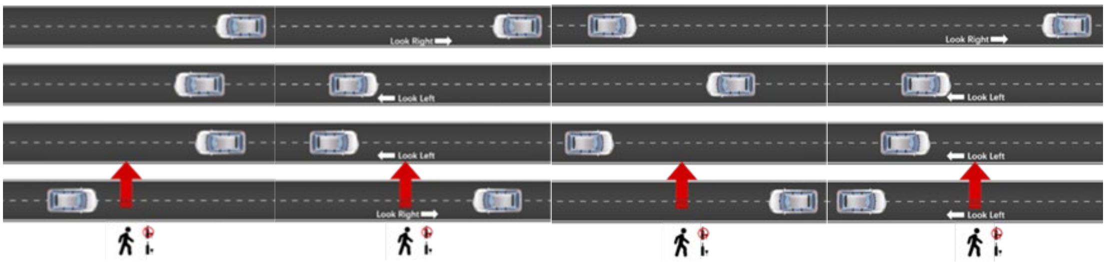


Fig. 1. Framework of research methodology.

3.1 Data collection

Using personal invitations, website registrations, campus emails, and posters, we attracted 60 individuals to participate in our experiment. Subsequently, a licensed medical practitioner conducted comprehensive health evaluations on these volunteers to determine their suitability for the study. The Alcohol Use Disorders Identification Test developed by Saunders et al. (1993) was employed to assess participants' patterns of alcohol consumption. This evaluation was crucial in ensuring the absence of alcohol allergies and confirming that participants satisfied the predefined selection criteria. Taking demographic distribution into account, 53 individuals (29 males and 24 females) were ultimately selected to participate in the street-crossing VR experiment. The ages of the participants ranged from 18 to 73 years, with a mean of 38.34 years and a standard deviation of 14.90 years.

An immersive VR environment was developed to simulate mid-block crossings in urban streets. This environment comprised 16 streets (4 scenes × 4 streets), each featuring distinct traffic settings such as randomized traffic direction, road marking, and time-to-collision (TTC) of traffic. The participants used shutter glasses and joysticks to navigate and interact within the VR environment. In the VR experiment, the participants were tasked with sequentially crossing all streets both before and after consuming alcohol. This required them to integrate surrounding environmental information, traffic speeds, and distance information to make informed crossing decisions. Fig. 2 illustrates the experimental scene design and Fig. 3 presents pedestrian crossing experiment conducted within the VR environment.



(a) Scene 1 (b) Scene 2 (c) Scene 3 (d) Scene 4

Fig. 2. Experimental design of all scenes: (a) scene 1; (b) scene 2; (c) scene 3; and (d) scene 4.

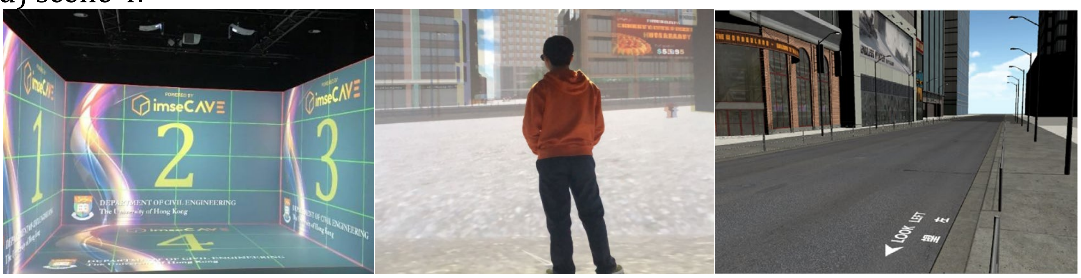


Fig. 3. Pedestrian interaction with the immersive VR environment.

Data regarding pedestrian behaviors during crossing stages were extracted for this study. Following data cleaning and preprocessing, 53 instances of Hong Kong pedestrians' crossing behaviors in the VR experiment before and after alcohol intake were collected. A summary of the data used in this study is presented in Table 1. Further details of the experimental design can be found in Ye et al. (2023).

Table 1 Data summary.

Name	Description	Mean	SD	Min	Max

TTC pedestrian	Time to conflict point of pedestrian(s)	6.60	1.61	3	24.72
TTC traffic	Time to conflict point of motor vehicle(s)	3.50	1.12	2	5
Road marking	1 = with road marking (i.e., 'look left' and 'look right') 0 = without road marking	0.50	0.50	0	1
Alcohol intake	1 = after alcohol intake 0 = before alcohol intake	0.50	0.50	0	1
Traffic direction	1 = traffic from the right side 0 = traffic from the left side	0.50	0.50	0	1

SD: standard deviation.

3.2 Reinforcement Learning

3.2.1 Preliminaries

RL is centered around the interaction between agents and their environments. It involves the process of acquiring knowledge on decision-making by mapping situations to actions to maximize a numerical reward signal. The learner is not furnished with explicit instructions on which actions to take; rather, the learner must explore different actions to ascertain which actions yield the highest rewards. In intricate scenarios, actions can have consequences not only for immediate rewards but also for future situations, thereby impacting all subsequent rewards (Sutton and Barto, 2018).

To model and address RL problems, the MDP is commonly used for modeling sequential decision-making problems. An MDP is defined by states, actions, transition probabilities, rewards, and a discount factor, known as the 5-tuple (S, A, P, R, γ). S is a finite set of states $\{1, 2, \ldots, N_S\}$ representing the condition or situation of the environment. A is a finite set of actions $\{1, 2, \ldots, N_A\}$ taken by an agent in a particular state. P is a set of conditional transition probabilities that describe the change in the environment's states when a particular action is taken, which captures the dynamics of the environment and how to respond to the agent's actions. R is a continuous set of possible rewards representing the immediate feedback or evaluation of an agent's action in a particular state, and $\gamma \in [0, 1)$ is the discount factor that determines the importance of future rewards relative to immediate rewards (Sutton and Barto, 2018).

In RL, understanding the goodness of a state is crucial for decision-making. Consequently, the value function, which denotes the expected return at state S following policy π, is defined in Eq. (1). This value function reflects the anticipated cumulative reward an agent can attain from a particular state by adhering to an optimal policy. Similarly, the Q function is used to assess the desirability of taking action a at state s, as formulated in Eq. (2).

$$V_\pi(s) = \mathrm{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \middle| S_t = s\right], s \in S \tag{1}$$

$$Q_\pi(s,a) = \mathrm{E}_\pi\left[\sum_{k=0}^{\infty}\gamma^k R_{t+k+1}\middle|S_t = s, A_t = a\right], s \in S, a \in A \quad (2)$$

Furthermore, the transition dynamics of the environment determine the next state given the current state and action, as formulated in Eq. (3). The reward function signifies the reward an agent can obtain by taking action a at state s, as expressed in Eq. (4).

$$P_{ss'}^a = P\left[S_{t+1} = s' \middle| S_t = s, A_t = a\right] \quad (3)$$

$$R_s^a = \mathrm{E}\left[R_{t+1} \middle| S_t = s, A_t = a\right] \quad (4)$$

Depending on whether the learning agent employs an environmental model, RL algorithms can be categorized into two main types: model-based and model-free. In the model-based approach, the agent learns transition dynamics and uses the knowledge to make decisions. Conversely, in the model-free approach, the agent lacks explicit information about transition dynamics and instead learns from the value function and policy function to guide its actions.

In this study, we meticulously designed the VR environment and formulated an MDP model with well-defined transition dynamics. By leveraging this known model, we can employ the model-based approach (e.g., value iteration), which offers the advantage of high sample efficiency and mitigates inaccuracies associated with unknown generative models of the environment. Moreover, the model-based approach aids in explaining how actions influence the system dynamics and better elucidates the agent's behavior.

3.2.2 Modeling pedestrian crossing behaviors

We developed an RL model to simulate sequential pedestrian crossing behaviors in a VR environment. In contrast to many existing studies that directly utilize various kinematic data (such as position, angle, speed, and acceleration) to construct the RL environment based on kinesiology dynamics, we adopted a more focused strategy. We extracted the data related to traffic settings and pedestrian crossing behaviors to build a RL environment with self-designed transition dynamics. This approach can address the specific research question while reducing computational costs.

To represent the RL environment, we used a discrete grid world framework, as depicted in Fig. 4.

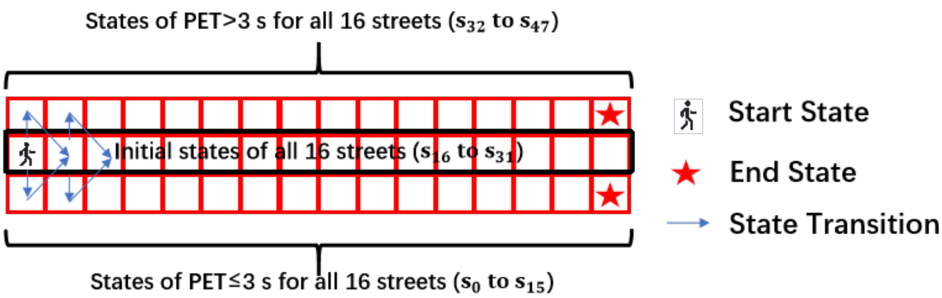


Fig. 4. Pedestrian crossing RL environment.

Each grid cell within the environment represents a distinct state, reflecting various traffic settings such as road markings, traffic direction, and the TTC of traffic. The second row of grid cells corresponds to the initial states of the 16 streets, while the first row consists of states with non-conflict or minor conflict (PET of > 3 s). The third row represents states with severe conflict (a PET of ⩽ 3 s), as established in previous studies (Kathuria and Vedagiri, 2020; Zhang et al., 2020). Notably, the first row of states represents pedestrians' safety states. Furthermore, under the specific settings in our experiment, the third row of states can signify pedestrians' states of reduced walking delay and increased efficiency, as demonstrated in Appendix A, Corollary 1. The state space is defined by Eq. (5), encompassing a total of 48 states. The agent's action involves determining the time required to reach the conflict point at each street, and the PET is precisely defined by Eq. (6). Moreover, the agent possesses complete knowledge of the transition dynamics within this environment. Algorithm 1 outlines the pseudocode used to compute the transition probabilities.

$$S = \{s_0, s_1, \ldots, s_{47}\} \tag{5}$$

$$PET = \left|TTC_{ped} - TTC_{traffic}\right| \tag{6}$$

Algorithm 1. Transition probability calculation

Input: $S, TTC_{ped}, TTC_{traffic}$
Output: P

for s_i in S:
  for s_j in S:
    if $s_i \in$ the 2nd row:
      $PET^i \leftarrow \left|TTC^i_{ped} - TTC^i_{traffic}\right|$
      if ($s_j \in$ the 1st row **and** $PET^i > 3$) **or** ($s_j \in$ the 3rd row **and** $PET^i \leq 3$):
        $p(s_j \mid s_i, TTC^i_{ped}) \leftarrow 1$
      else
        $p(s_j \mid s_i, TTC^i_{ped}) \leftarrow 0$
    else
      if ($s_j \in$ the 2nd row) **and** (s_j in the next column of s_i):
        $p(s_j \mid s_i) \leftarrow 1$
      else
        $p(s_j \mid s_i) \leftarrow 0$
return P

To simulate the pedestrian crossing behaviors within this environment, the agent commences its journey from the first grid cell of the second row and sequentially crosses the 16 streets until it reaches the final grid cell of either the first or third row, contingent upon the specific actions taken. The precise rewards linked to the model are initially unknown and require estimation. The reward function, denoted as $R = \omega^* \phi(s)$, is defined as the product of ω^* (the weight to be estimated) and $\phi(s)$, which represents a linear function of state s.

3.2.3 Value iteration

Under the assumption that we had recovered the reward function through IRL, the next step was to validate the effectiveness of the estimated reward function R. To achieve this, the RL algorithm guided by R was used to train the agent and simulate real pedestrian behaviors. Consistency between the agent's behaviors and expert demonstrations indicates that the restored reward function accurately represents true pedestrian motivations and validates the adopted IRL methods. Given the nature of the problem in this study, a model-based method, namely value iteration, was employed to obtain the optimal policy under the reward function R (Algorithm 2).

Algorithm 2. Value iteration

Input: MDP tuple (S, A, P, R, γ), small positive number θ

Output: optimal policy π^*

1. **for** s in S:
2. $\quad V(s) \leftarrow 0$
3. $\Delta \leftarrow 0$
4. **while** $\Delta > \theta$:
5. $\quad$ **for** s in S:
6. $\qquad v \leftarrow V(s)$
7. $\qquad V(s) \leftarrow \max_{a \in A} \sum_{s' \in S, r \in R} p(s', r \mid s, a)(r + \gamma V(s'))$
8. $\qquad \Delta \leftarrow \max(\Delta, |v - V(s)|)$
9. **for** s in S:
10. $\quad \pi^*(s) \leftarrow \arg\max_{a \in A} \sum_{s' \in S, r \in R} p(s', r \mid s, a)(r + \gamma V(s'))$
11. **return** π^*

Value iteration is a fundamental algorithm in RL that enables an agent to solve an MDP by iteratively estimating the optimal value function, which satisfies the Bellman optimality equation as shown in Eq. (7) and (8). In value iteration, the agent repeatedly updates the value of each state within MDP until convergence is achieved. This iterative procedure ensures that the agent progressively refines its estimate of the optimal value function, leading to an improved policy. By computing the optimal value function, the agent can ascertain the optimal actions to take in each state, thereby resulting in an optimal policy that maximizes the expected cumulative reward. Value iteration offers a methodical and efficient approach to addressing MDPs, enabling the agent to make well-informed decisions in complex environments characterized by uncertain outcomes.

$$V^*(s) = \max_{a \in A} \mathrm{E}\left[R_{t+1} + \gamma V^*(S_{t+1}) \middle| S_t = s, A_t = a \right] \tag{7}$$

$$V^*(s) = \max_{a \in A} \sum_{s' \in S, r \in R} p(s', r \mid s, a)(r + \gamma V^*(s')) \tag{8}$$

3.3 Inverse Reinforcement Learning

3.3.1 Preliminaries

IRL aims to retrieve the reward function from expert demonstrations and then use the reward to derive a policy that results in behaviors similar to the demonstrations. It is assumed that the reward is solely determined by the state, that is, $R_i = R(s_i)$. Let $\zeta = \left[(s_1, a_1), (s_2, a_2), \ldots\right]$ the path taken by an agent, and the total reward of the path can be expressed as:

$$R(\zeta) = \sum_{(s_i, a_i) \in \zeta} R(s_i) \tag{9}$$

Let $\phi: S \to \mathbb{R}^D$, where D is the dimension of the feature space. The feature vector of state s is $\phi(s)$, and the feature counts of path ζ are formulated as:

$$\phi_\zeta = \sum_{(s_i, a_i) \in \zeta} \phi_{s_i} \tag{10}$$

The feature expectation can then be expressed as:

$$\tilde{\phi} = \sum_{\zeta} P(\xi) \phi_\zeta \tag{11}$$

If the recovered reward function can effectively explain expert demonstrations, the feature expectations of observed paths and optimal paths should exhibit similarity, as depicted in Eq. (12).

$$\mathrm{E}[\phi_\zeta] = L[\phi_\zeta] \tag{12}$$

Unfortunately, feature matching is ambiguous, as each policy can be optimal for multiple reward functions, and multiple policies can lead to the same feature counts (Ziebart et al., 2008). To address this ambiguity, MaxEnt IRL algorithms were introduced.

3.3.2 MaxEnt IRL

Given the stochastic nature of the environment, multiple paths have the potential to align with feature expectations, and these paths may possess additional constraints beyond those implied by the feature expectations. To address this challenge, MaxEnt IRL introduces a maximum entropy distribution over paths. The entropy distribution minimizes the imposition of extra constraints beyond the information derived from feature expectation matching, as formulated in Eq. (13).

$$\begin{aligned} &\arg\max_p H(p) = -\sum_{\zeta} p(\zeta) \log p(\zeta) \\ &s.t.\ E[\phi_\zeta] = L[\phi_\zeta] \\ &\sum_{\zeta} p(\zeta) = 1,\ \forall \zeta : p(\zeta) > 0 \end{aligned} \tag{13}$$

Consequently, paths that yield higher total rewards are exponentially more likely to be chosen, as indicated in Eq. (14).

$$p(\zeta) = \frac{1}{z} \exp(R(\zeta)) \tag{14}$$

where z is the partition function. The reward is parameterized by weights ω:

$$p(\zeta \mid \omega) = \frac{1}{z(\omega)} \exp(\omega^T \phi_\zeta) \prod_{s_{t+1}, a_t, s_t \in \zeta} p_{s_t s_{t+1}}^{a_t} \tag{15}$$

The observed feature expectation from N observed trajectories is given as:

$$\tilde{\phi} \approx \tilde{\phi}_{obs} = \frac{1}{N} \sum_{i=1}^{N} \phi_{\zeta_i} \tag{16}$$

Maximum likelihood estimation is performed to determine the optimal reward weights ω^*, as formulated in Eq. (17). The gradient of the log-likelihood function is expressed in Eq. (18). The top-level design of MaxEnt IRL is presented in Algorithm 3.

$$\omega^{*} = \arg\max_{\omega} L(\omega) = \arg\max_{\omega} \sum_{i=1}^{N} \log p(\zeta_i \mid \omega) \tag{17}$$

$$\nabla L(\omega) = \tilde{\phi} - \sum_{i=1}^{N} p(\zeta_i \mid \omega)\phi_{\zeta_i} = \tilde{\phi}_{obs} - \sum_{s_i \in S} D_{s_i}\phi_{s_i} \tag{18}$$

Algorithm 3. MaxEnt IRL

Input: MDP / R, expert trajectories ζ, features ϕ

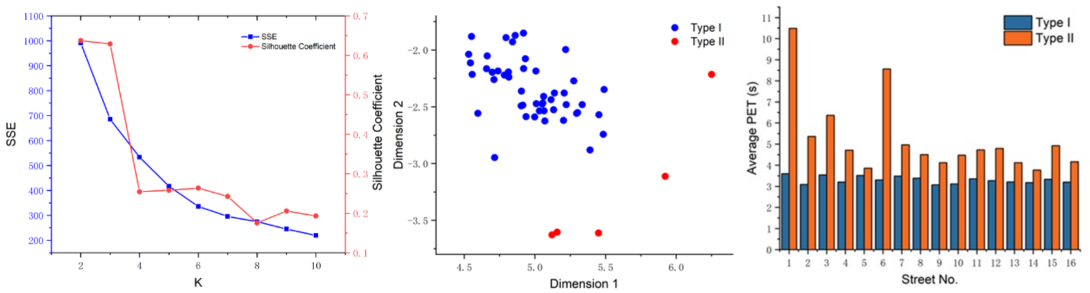
Output: Reward R

1. Compute feature expectations $\bar{\phi}$ with ζ and ϕ
2. Initialize the weights ω
3. **repeat**
4. Find reward R_ω under ω and ϕ
5. Find the expected state visitation frequency D under R_ω and P
6. Find the gradient under $\bar{\phi}$, ϕ, and D
7. Update weights ω
8. **until convergence**

4. Results

4.1 Clustering analysis results

In the VR experiment, each pedestrian executed 16 crossing actions, leading to 16 pedestrian–vehicle interaction outcomes. To detect similar patterns among pedestrians, 53 participants were grouped into multiple clusters using the K-means algorithm, according to their PET values across all traffic scenarios under a sober condition. The number of clustering groups was determined by evaluating the silhouette coefficient and the sum of squared errors (SSE). As Fig. 5(a) shows, while the SSE curve did not exhibit a distinct elbow point, the silhouette curve indicated that the pedestrians should be classified into two types. To visualize the clustering points in two dimensions, the *t*-distributed Stochastic Neighbor Embedding (t-SNE) algorithm was used, as illustrated in Fig. 5(b). The average PET values for the two types are also presented in Fig. 5(c). These results explicitly support the classification of pedestrians into two types, illustrating their distinct preferences when making crossing decisions and reflecting their respective tendencies toward risky and cautious behaviors. Type I, totaling 48 pedestrians, exhibited a propensity for risk-taking, while type II pedestrians, comprising five individuals, demonstrated a cautious style.



(a) (b) (c)

Fig. 5. Results of clustering analysis: (a) curve of SSE and silhouette coefficient; (b) t-SNE results; and (c) average PET values.

To gain deeper insights into the characteristics of cautious and risky pedestrians, demographic traits were compared using the t-test and Fisher's exact test. Tables 2 and 3 reveal significant differences in demographic characteristics between type I and type II pedestrians. Specifically, compared to the cautious group, the risky was characterized by a lower age (significant at the 1% level) and a higher level of education (significant at the 10% level).

Table 2. Results of independent samples *t*-test of demographic variables between type I and type II pedestrians.

Demographic variables	Interpretation	Mean (standard deviation)		*p*-value
		Type I	Type II	
Age	Age of pedestrians, ranges from 18 to 73	36.23 (14.02)	58.60 (3.68)	0.000***

*** Significant at the 1% level.

Table 3. Results of Fisher's exact test of demographic variables between type I and type II pedestrians.

Demographic variables	Interpretation	Frequency		*p*-value
		Type I	Type II	
Gender	0: female	21	3	0.649
	1: male	27	2	
Education	1: primary	0	0	0.059*
	2: forms 1–3	2	0	
	3: forms 4–7	4	3	
	4: tertiary level	14	1	
	5: postgraduate degree	27	1	
	6: doctoral degree	1	0	
Driver license	0: no	25	2	0.669
	1: yes	23	3	

* Significant at the 10% level.

4.2 Results of Inverse Reinforcement Learning

Given the clustering outcomes, the IRL approach was used to recover reward functions for the two categories of pedestrians, thereby revealing their distinct motivations regarding safety and efficiency. The computed reward maps for all states, covering the four scenarios involving pedestrian types under varying drinking conditions, are illustrated in Fig. 6. As aforementioned in Section 3.2, the rewards assigned to the first row of states represent safety-oriented motivations of pedestrians, while the rewards assigned to the third row of states indicate efficiency-oriented motivations.

A comparison of the two pedestrian types revealed that type II pedestrians exhibited a stronger propensity toward safety and a weaker inclination toward efficiency compared with type I pedestrians, both before and after alcohol consumption. Under the sober condition, both pedestrian types showed a heightened emphasis on safety motivations, although type II pedestrians displayed a slightly higher preference for safety over efficiency. However, both types of pedestrians under the influence exhibited a noticeable shift in motivations from safety to efficiency. Additionally, varying degrees of motivation shifts between safety and efficiency occurred, and these shifts varied across different traffic scenarios. Notably, for type I pedestrians under the influence of alcohol, the motivation for efficiency exceeded that for safety in most traffic scenarios, whereas type II pedestrians, even those under the influence of alcohol, maintained a stronger emphasis on safety.

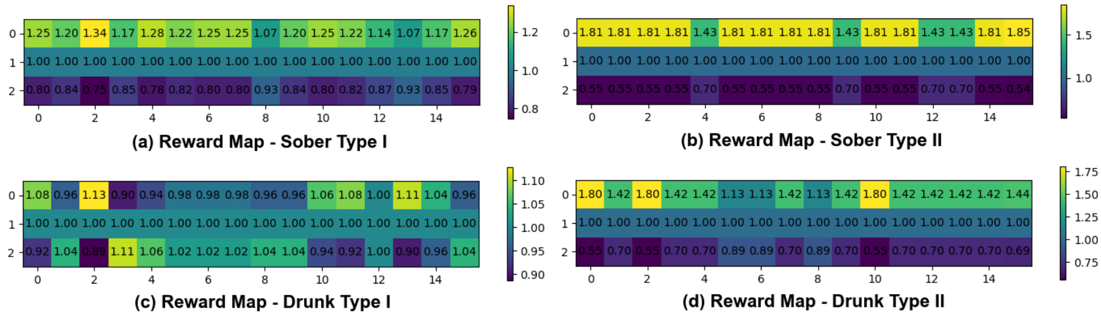


Fig. 6. Recovered reward maps from pedestrian crossing behaviors: (a) sober type I; (b) sober type II; (c) drunk type I; and (d) drunk type II.

Fig. 7 illustrates the rewards obtained with and without road markings, while Fig. 8 presents the rewards associated with the left and right traffic directions. Additionally, Fig. 9 displays the rewards before and after alcohol intake. Across all cases under investigation, the differences in rewards between scenarios with and without road markings were statistically non-significant (p-value > 0.05). This suggests that road markings have minimal impact on pedestrian motivations regarding safety and efficiency. Regarding the influence of traffic direction, statistically significant differences (p-value = 0.031 and 0.030 for states of PET ≤ 3s and PET > 3s, respectively) in rewards between traffic approaching from the left and right were observed only among sober type II pedestrians. This indicates their ability to adapt their motivations according to the direction of traffic, aligning with their cautious nature. However, this difference became statistically non-significant when the pedestrians were in a drunken condition (p-value = 0.369 and 0.579 for states of PET ≤ 3s and PET > 3s, respectively). Furthermore, for both pedestrian types, the differences in rewards between sober and drunken conditions were highly significant, with a significance level of 1% (p-value < 0.01 shown as Fig. 9).

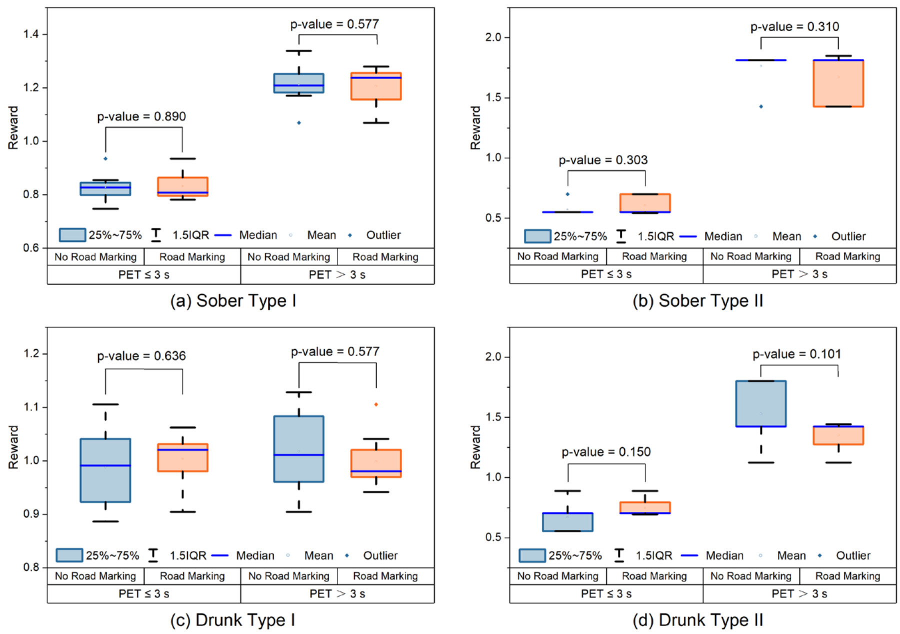


Fig. 7. Rewards in scenarios with and without road markings.

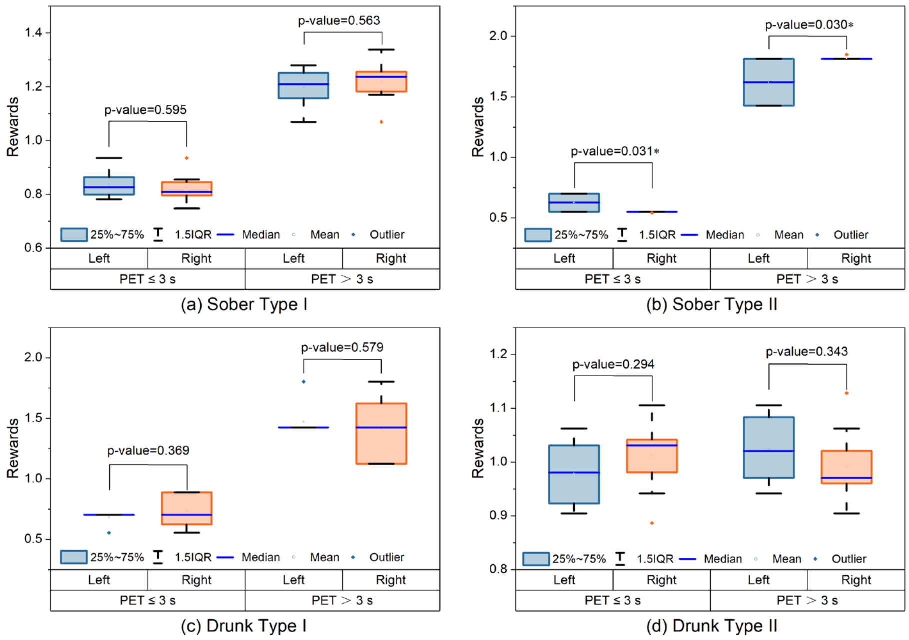


Fig. 8. Rewards in scenarios of different traffic directions.

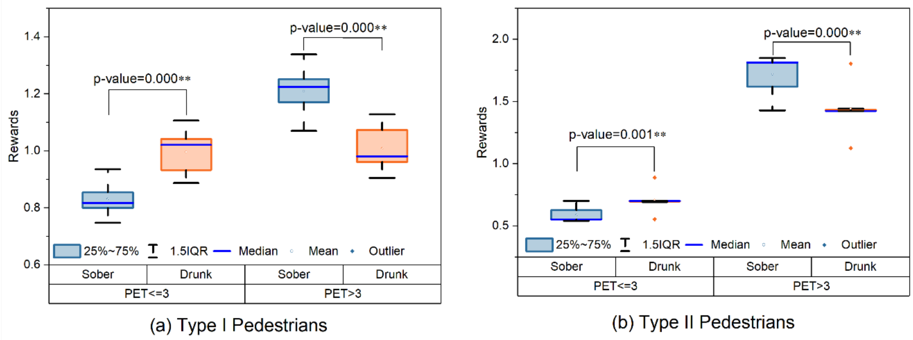


Fig. 9. Rewards in scenarios with sober and drunken pedestrians.

Fig. 10 illustrates the rewards associated with different TTC values for traffic and pedestrians. A noticeable distinction existed between the two types of pedestrians, with type II pedestrians generally exhibiting a greater motivation to choose a higher TTC of pedestrians when making crossing decisions, compared with type I pedestrians. This implies that type II pedestrians prioritized a larger safety margin and exercised more caution in their decision-making process when crossing the road.

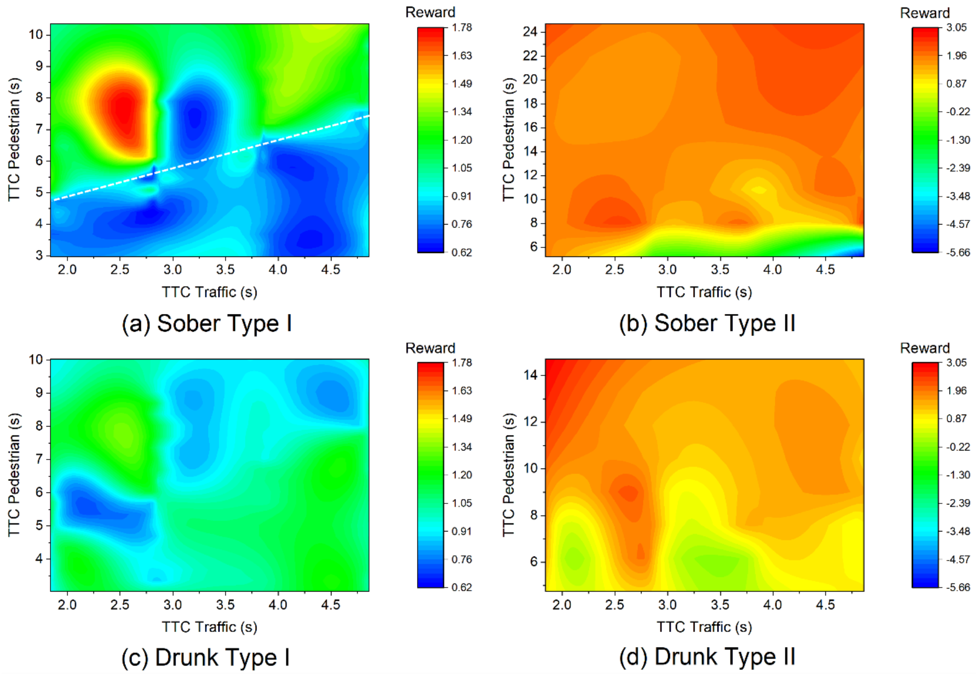


Fig. 10. TTC of traffic and TTC of pedestrian rewards: (a) sober type I; (b) sober type II; (c) drunk type I; and (d) drunk type II.

Under sober conditions, type I pedestrians exhibited a distinct demarcation in reward distribution. A boundary existed between high-reward and low-reward regions. The significant difference in rewards on either side of this boundary line suggests that as soon as pedestrians perceive the situation as safe, they promptly decide to cross. Although these pedestrians presumably prioritize efficiency, safety remains a substantial concern. Nevertheless, when they perceive the crossing as safe, their motivation to minimize crossing time becomes more pronounced. For instance, when the TTC of traffic fell between 3s and 3.5s, a sudden shift in rewards occurred within the region characterized by a higher TTC of pedestrians. This indicates that pedestrians with an initial TTC of 3s preferred to wait longer, as they perceived the immediate crossing as unsafe. However, the accurate determination of a safe crossing time is crucial. The demarcation line was typically around a 3s difference between the TTC of traffic and the TTC of pedestrians, sometimes even less. This situation can result in traffic conflicts and pose risks to pedestrians. In contrast, for type II pedestrians, the high rewards were concentrated in the region of high TTC of pedestrians. However, rewards abruptly declined when the TTC of pedestrians reached approximately 6–7s, indicating a strong motivation for safety and a shallow motivation for efficiency.

Under the influence of alcohol, both types of pedestrians exhibited significant changes in rewards. Type I pedestrians no longer exhibited a clear demarcation line, and the rewards in the original region below the dividing line became substantially higher, while certain regions with a high TTC of pedestrians demonstrated lower rewards. Interestingly, when the TTC of traffic ranged from 2 to 3s, the reward patterns fluctuated between high, low, and high again as the TTC of pedestrians increased. The initial high-reward region below the dividing line revealed the pedestrian motivation for efficiency, even in traffic conflicts. The second region, corresponding to low rewards, and the third region, corresponding to high rewards, indicate the pedestrian motivation for safety, although the pedestrians' judgment of the appropriate safe crossing time was inadequate. For type II pedestrians, the rewards associated with a high TTC also decreased under the influence of alcohol. Nevertheless, the pedestrians still exhibited a strong motivation for safety and a weak motivation for efficiency. Overall, the influence of alcohol caused a shift in motivation from safety to efficiency to some extent for both types of pedestrians.

4.3 Model validations

After the recovery of the reward function, the RL algorithm was used to derive the optimal policy and facilitate agent training to maximize rewards. The primary role of RL here was to validate the effectiveness of the recovered reward function. The validation was conducted through a comparative analysis of the observed behavior and the behavior exhibited by experts. Such evaluation enables us to assess whether the recovered reward function adequately elucidates the pedestrian crossing behaviors.

The feature expectations of well-trained agents under the optimal policy and those of both cautious and risky pedestrians under sober and drunken conditions are depicted in Fig. 11. A close resemblance occurred between the feature expectation distributions of agents and pedestrians, indicating a certain level of similarity.

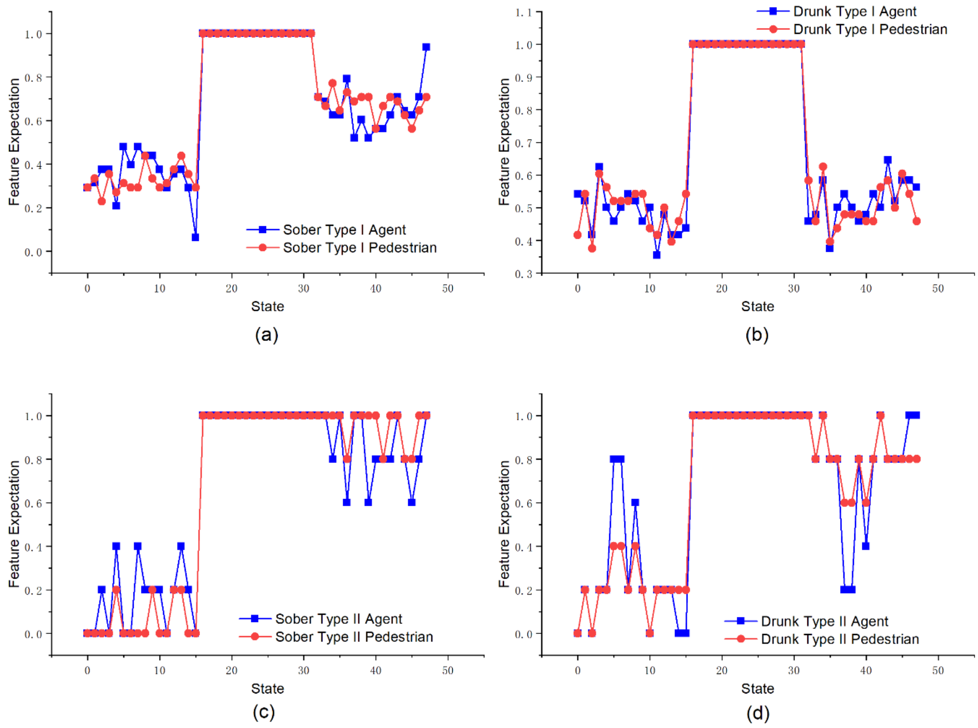


Fig. 11. Feature expectations of agents and pedestrians: (a) type I under sober condition; (b) type II under sober condition; (c) type I under drunken condition; and (d) type II under drunken condition.

To quantitatively assess the similarity between these distributions, Kullback–Leibler (KL) and Jensen–Shannon (JS) divergences were computed for the aforementioned. The KL divergence ranges from 0 to infinity, while the JS divergence ranges from 0 to 1. A smaller value for both divergences signifies a higher similarity degree between the distributions. According to Table 4, the behavior of the RL agents trained using the recovered reward functions was closely aligned with the pedestrian behavioral data, indicating the effectiveness of the RL algorithm in achieving satisfactory training results. Moreover, the IRL algorithm successfully recovered the reward functions, revealing pedestrian motivations and generating policies that emulate pedestrian behaviors.

Table 4. KL divergence and JS divergence between agents and pedestrians.

Type	Condition	KL divergence	JS divergence
Type I	Sober	0.0066	0.0016
	Drunk	0.0035	0.0009
Type II	Sober	0.0496	0.0160
	Drunk	0.2830	0.0107

5. Discussions

5.1 Differences between risky and cautious types

The classification of pedestrians into risky and cautious types was based on the clustering analysis of PET during pedestrian–vehicle interactions at mid-block crossings. The results showed that the number of risky pedestrians surpassed that of cautious ones. One reason for the imbalance is that elderly individuals are relatively difficult to reach and recruit for VR experiments. Due to ethical concerns, only a small number of elderly participants were selected after health evaluations, resulting in an unbalanced age distribution. Despite that, the results indeed revealed significant differences in demographic factors between the pedestrian types, in terms of age and education. These findings are consistent with previous research. For example, older pedestrians were more cautious than younger pedestrians, presumably owing to the factors such as declining physical abilities, accumulated experiences, fear of injuries, and cognitive changes (Bernhoft and Carstensen, 2008; Ye et al., 2020; Aghabayk et al., 2021; Zeng et al., 2023). Furthermore, pedestrians with higher education levels also tended to exhibit risky behaviors, consistent with prior research indicating a positive association between educational level and traffic violations (Useche et al., 2021).

The safety–efficiency trade-off is a pervasive issue that considerably varies among pedestrians (Zhu et al., 2021). Through the clustering process, distinct types of pedestrians were established, enabling the identification of shared characteristics that influence decision-making in the context of the safety–efficiency trade-off. The IRL analysis results demonstrated considerable disparities in safety and efficiency motivations between pedestrians categorized as risky and cautious. Notably, the cautious type emphasized safety more than the risky type. Interestingly, even among the risky type, safety motivations remained more pronounced than efficiency motivations under sober conditions. This suggests that prioritizing safety precedes the pursuit of efficiency, and this is related to the establishment of safe communities. In an ideal scenario, this approach would yield no complications and may even significantly reduce travel time. However, the outcomes revealed the existence of misjudgments, attributable to an eager desire for time-saving or inherent limitations in perceptual or motor abilities. These misjudgments frequently trigger traffic conflicts. These findings underscore the imperative of addressing the underlying factors contributing to misjudgments and devising strategies to enhance pedestrian decision-making processes. Furthermore, the findings emphasize the necessity of implementing effective interventions and improving infrastructure to foster safer environments for pedestrians, irrespective of their risk inclination.

5.2 Effect of alcohol on crossing motivations

The influence of alcohol on pedestrian behaviors was a primary focus of this study, considering the well-established association of alcohol with human errors and traffic accidents. The results revealed a significant alteration in the mental motivations of risky and cautious pedestrians under the influence of alcohol, as their motivations shifted from safety to efficiency. This finding aligns with previous research, which reported impaired cognitive abilities under drunken conditions (Oviedo-Trespalacios et al., 2021).

Despite alcohol leading to a motivation shift in both types of pedestrians, the effects were markedly different. For cautious pedestrians, safety motivations remained significantly stronger than efficiency motivations. Consequently, they were less likely to exhibit aggressive and risky crossing behaviors, indicating the preservation of safety-oriented mental attitudes.

Conversely, the impact of alcohol on risky pedestrians was critical. Under sober conditions, safety motivations were marginally stronger than efficiency motivations. However, under the influence of alcohol, the balance between safety and efficiency shifted in favor of the latter. This shift implies that the primacy of safety considerations diminished, potentially leading to an increased propensity for aggressive and risky crossing behaviors. Previous studies have reported a significant association between impulsivity in alcohol-dependent individuals and risky behaviors (Cooper et al., 2000; Jakubczyk et al., 2013). The effect of alcohol on aggressive behaviors varies among individuals. For example, White et al. (2013) found that increased alcohol consumption was more strongly linked to increased aggressive behaviors among boys with attitudes favoring violence and those living in high-crime neighborhoods. Additionally, alcohol increased aggression for both males and females, but this effect was more pronounced for males (Giancola et al., 2009).

Moreover, the previously observed division between high-reward regions for high TTC of pedestrians and low-reward regions for low TTC of pedestrians disappeared under the influence of alcohol. This signifies that the underlying premise of prioritizing safety was no longer valid. Consequently, the alcohol-induced motivation shift played a crucial role in altering pedestrians' actual crossing behaviors, potentially leading to severe traffic conflicts or even accidents.

5.3 Effect of traffic environment on crossing motivations

The influence of traffic contextual factors was also examined to elucidate pedestrian motivations comprehensively. Despite being a prominent traffic sign in Hong Kong, the road markings of "look left" and "look right" demonstrated an insignificant effect on altering pedestrian crossing motivations. This might be attributable to the static nature of road markings, which merely indicate the traffic direction without assisting pedestrians in dynamically assessing the approaching vehicles and determining a safe gap. Thus, more effective traffic facilities that enhance pedestrian cognitive abilities during crossing should be considered.

Our study also revealed that traffic directions significantly altered the motivations of cautious pedestrians under sober conditions. The pedestrians exhibited higher safety motivations when traffic approached from the right-hand side than when traffic came from the left-hand side. This is due to the familiarity of Hong Kong pedestrians with the left-driving system, which leads them to anticipate traffic approaching from the right-hand side. However, this difference in motivations became insignificant when pedestrians were under the influence of alcohol.

In terms of TTC, even pedestrians with a propensity for risky behavior exhibited strong safety motivations when the TTC of traffic closely aligned with the TTC of pedestrians under sober conditions. This suggests that pedestrians could temporarily adjust their motivations in critical situations. However, this adaptive capability diminished when pedestrians were intoxicated, exposing them to heightened risks.

5.4 Limitations and future studies

This study introduced a novel IRL framework to estimate pedestrian crossing motivations of safety and efficiency under the influence of alcohol. The research gained insights into risky and cautious crossing behaviors, demographic factors, and traffic environmental factors from the perspective of mental motivations. Despite the contributions of this study, it has certain limitations.

First, to facilitate comparative analysis and ensure the safety of participants who are under the influence of alcohol, a VR experiment was conducted to collect pedestrian behavioral data. The effectiveness of this emerging approach has been widely acknowledged (Deb et al., 2017; Ye et al., 2020; Kown et al., 2022). However, this method may introduce biased behaviors, as participants did not encounter real risks during the street crossing tasks. Thus, their risky behaviors might be exaggerated in the simulated environment.

Second, given the heterogeneity and randomness of pedestrian behaviors, the attempt to understand individual pedestrians' motivations in isolation is meaningless, as different individuals may exhibit heterogeneous behaviors even under similar scenarios. Therefore, the pedestrians were classified into two homogenous groups to capture common crossing motivations. However, the imbalanced clusters resulting from a limited sample size may compromise the reliability of the results, especially for the cautious pedestrian group. Future studies should explore more effective data collection methods to increase the sample size. This would enable a more detailed examination of individual crossing behaviors in conjunction with factors such as personality traits, safety attitudes, and other socio-demographic characteristics.

Third, our experiment did not capture many potentially influential factors. Due to the simulator sickness associated with VR and ethical concerns related to intoxication, we had to control the experiment duration by limiting the number of scenarios. Furthermore, incorporating too many features without sufficient samples is not technically sound, due to the curse of dimensionality. Future studies should investigate the effects of additional factors such as weather conditions, traffic characteristics, and pedestrian group size, among others.

Lastly, to better elucidate the influence of key factors and distinguish between safety and efficiency states, we modeled pedestrian crossing as a discrete RL environment. Although this approach reduces complexity and computational costs, generalizing findings to unseen environments might be challenging. In addition, the algorithms used in this study were based on clustered data and may not be suitable for prediction tasks. Future studies should develop more advanced IRL algorithms designed for continuous environments, tailored to the specific research problems at hand.

6. Conclusions

In this study, we estimated pedestrians' safety and efficiency motivations before and after drinking by analyzing their crossing behaviors using VR experiment data. Given the inherent randomness of pedestrian behaviors, we employed a clustering algorithm to classify pedestrians into two distinct types. Subsequently, an IRL approach was proposed to recover reward functions from pedestrians' crossing demonstrations. This approach acted as a surrogate method to reveal the unobserved motivations guiding pedestrian behavior. According to the recovered reward functions, the RL algorithm was then used to learn optimal policies and train agents to simulate pedestrians' crossing behaviors, which provided an effective means to validate the reliability of IRL results.

The findings of this study revealed significant differences in safety and efficiency motivations between the two types of pedestrians. Risky pedestrians demonstrated a stronger motivation for efficiency over safety, whereas cautious pedestrians exhibited a preference for safety motivations. The risky pedestrians were characterized by lower age and a higher education level. Under the influence of alcohol, both types of pedestrians exhibited a shift in motivation from safety to efficiency. However, the cautious type maintained a higher motivation for safety than efficiency, while the risky type exhibited a slightly higher motivation for efficiency than for safety, potentially leading to more aggressive crossing behaviors. The motivation patterns, the TTC of traffic, and the TTC of pedestrians were also revealed. Risky pedestrians tended to misjudge the safe crossing time owing to their strong inclination toward efficiency, which would lead to severe traffic conflicts and cause potential danger. Furthermore, in terms of traffic environmental factors, road markings did not significantly influence the motivations of both pedestrian types. However, traffic direction greatly affected cautious pedestrians under sober conditions. The reliability of the IRL results was successfully confirmed through the high level of similarity between the crossing behaviors of trained agents and pedestrians. This validation approach effectively comprehends pedestrian motivations and can be applied to similar problems in future studies.

According to the findings on pedestrians' motivations for safety and efficiency under the influence of alcohol, countermeasures should be considered to mitigate the problem of drunk walking and risky crossing behaviors. In terms of engineering, infrastructure enhancements such as improved lighting, clearer signage, and more pedestrian-friendly road designs could potentially help create safer environments for alcohol-impaired pedestrians. Emerging technologies may also offer opportunities for improving pedestrian safety. For example, wearable devices could be used to alert pedestrians about potential hazards or when it is safe to cross a street, and applications that provide real-time traffic information and safe crossing times at intersections could assist pedestrians in making safer decisions. From an educational perspective, traffic management agencies could implement programs to help pedestrians better understand traffic rules, the adverse effects of alcohol on decision-making, and the importance of prioritizing safety over efficiency. These programs could potentially change the mindset of risky pedestrians and reduce the likelihood of misjudgments. In terms of enforcement, regulations against drunk walking could be considered, but more efforts are needed to gain social acceptance. In addition, efforts should be directed toward promoting a change in pedestrians' mental attitudes and motivations. This shift could result in more pedestrians transitioning from a risky to cautious type, ultimately reducing risky crossing behaviors and enhancing the overall safety of pedestrian-vehicle interactions.

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Appendix A

Corollary 1. The walking delay during pedestrian–vehicle interactions with a $PET \le 3s$ must be less than that with a $PET > 3s$ under the following experimental settings:

(1) $TTC_{traffic} \in \{2s, 3s, 4s, 5s\}$;

(2) $TTC_{ped} \ge 3$.

Proof

When $PET \le 3$,

$\because \left|TTC_{ped} - TTC_{traffic}\right| \le 3$

$\therefore -3 \le TTC_{ped} - TTC_{traffic} \le 3$

$\therefore TTC_{traffic} - 3 \le TTC_{ped} \le TTC_{traffic} + 3$

$\because TTC_{traffic} - 3 \le 2 < 3$

$\therefore 3 \le TTC_{ped} \le TTC_{traffic} + 3$

Similarly, for $PET > 3$,

$\because \left|TTC_{ped} - TTC_{traffic}\right| > 3$

$\therefore TTC_{ped} - TTC_{traffic} > 3$ or $TTC_{traffic} - TTC_{ped} > 3$

$\therefore TTC_{ped} > TTC_{traffic} + 3$ or $TTC_{ped} < TTC_{traffic} - 3$

$\because TTC_{ped} > 3$

$\therefore TTC_{ped} < TTC_{traffic} - 3$ does not hold.

$\therefore TTC_{ped} > TTC_{traffic} + 3$

Hence, we can represent the TTC of pedestrians for these two cases, as shown in Fig. A1. From this, we can conclude that in the particular setup of this experiment, the pedestrian walking delay was lower for the case with $PET \le 3$ compared with the case with $PET > 3$, indicating higher efficiency.

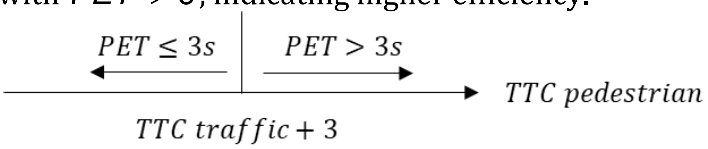

Fig. A1. Range of TTC pedestrian for two cases.