THE INFLUENCE OF DISTRACTIONS, ACCOMPANIMENT TYPE, VEHICLE TYPE, AND STRESS ON PEDESTRIANS' WAITING TIME: APPLICATION OF IMMERSIVE VIRTUAL REALITY (IVR) AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

This study aimed to test the influence of different distractors, vehicle types, and stress on pedestrian waiting time at unsignalized intersections. The data was obtained in 2019 through immersive virtual reality, in which 32 combinations of the possible environments were tested. Distractors were visual and phone distractions, and accompaniment by a kid. These were tested in environments with different traffic volumes and vehicle types, either traditional or automated vehicles (AVs). Regularized Gradient Boosting Tree (XGBoost) and Restricted Boltzmann Machine techniques were used to predict the waiting time. Associations between the predicted waiting time and other variables were analyzed using a Cox Proportional-Hazards model. The results showed that distractors with the biggest impact were looking at visual distractions and looking at a billboard while waiting, which increased waiting time. Other factors were mean acceleration and mean deceleration, where acceleration increases waiting time, and deceleration decreases it. At last, an increase in safety (i.e., higher PET) leads to a lower waiting time. Remarkably, the most significant effects were seen with traditional cars, which could be due to different sentiments about AVs.

Keywords: Pedestrian Waiting Time, Crossing Unsignalized Intersection, Stress, Smartphone Distraction, Visual Distraction

INTRODUCTION

Overview

Pedestrians are the most vulnerable road users in accidents. A big cause of accidents is distractions, which misguide attention. Many studies have confirmed the negative effects of mobile phone usage on traffic behavior and use of cell phones while driving is prohibited. Another type of distractor is visual and auditory distractions. Visual distractions, like billboards, make people look away from the road. Auditory distractions, like talking with another person or listening to music, also have negative impacts (Tapiro, Oron-Gilad, & Parmet, 2018). The last type of distraction is accompaniment. In pedestrian behavior, research found that accompanied adults change their behavior negatively with other adults, but positively with children (Arman, Rafe, & Kretz, 2019). Adult accompaniment positively influences children (O’Neal, Jiang, Brown, Kearney, & Plumert, 2019).

Distractors have different levels of impact (Antić, Pešić, Milutinović, & Maslać, 2016). By researching this impact, necessary measures to improve traffic safety become clearer. Most focus on one distractor, but distractors can have different impacts when put together (Antić et al., 2016). However, comparisons between the distractors are limited, and therefore, this study will address this point. This contributes to stakeholders designing roads to be able to prioritize safety measures and choose those with bigger impacts.
Stress is another road user influence. Stress has a big impact on people, but also on-road usage. Life changes and subjective stress have significant effects on the risk of traffic accidents (SELZER & VINOKUR, 1974). Pedestrians with lower stress levels exhibit safer crossing behavior (Zheng, Qu, Ge, Sun, & Zhang, 2017). However, it is unknown how beforementioned distractions impact stress on pedestrians. Because of increased stress levels in today's society, it is important to find out how stress impacts crossing behavior of pedestrians.
These impacts could have an influence on crossing behavior, or waiting time, the time pedestrians wait before initiating crossing, and therefore on pedestrian safety. For example, by adjusting waiting time of red lights, rates of violations could be decreased. Also, predicting waiting time contributes to safer interactions with (automated) vehicles by making anticipation easier and decreasing the risk of road accidents. Some have analyzed waiting time (Kalatian & Farooq, 2019; Kalatian, Sobhani, & Farooq, 2020), but there is more research needed to study other influencing factors.
Automated vehicles (AVs) are increasingly joining roads, which makes studying pedestrian behaviors and interactions important. Studies on this contribute to development of better technology systems for AVs and better integration of AVs into society. Two challenges are interactions of AVs with other road users and sentiments towards AVs. Knowing better how other road users will react to AVs helps developing good software for AVs and knowing sentiments towards AVs helps identifying and addressing potential problems for integration.
Virtual reality (VR) is up-and-coming technology, where you observe computer-generated environments. Immersive VR (iVR) includes other senses, like touch and sound. In transport research, this tool has gained popularity because of its ability to test dangerous situations without needing participants to take risks.

Current Study Context

This study analyses pedestrians' waiting times. It is essential to know which factors influence waiting time because it also influences other factors, but most importantly safety. In general, waiting time seems to have positive effects on pedestrian safety (Arman et al., 2019). However, studies focussing on waiting time are limited.
The study uses an unsignalized intersection, so participants must decide on their own waiting time. The distractions explored in this study are visual, phone, and accompaniment. Most studies focus on one of three distraction types. Here, the effects of these distractors are measured separately and combined. The visual distractions are billboards and firetrucks, phone distractions consist of solving mazes on phones, and the accompaniment will be a child. External variables and internal variables, like eye movements and stress levels, are measured too. Studies that have measured effects of accompaniment have measured it compared to other children or adults, but not the effect of children on adults, especially not with waiting time.
The data used comes from (Hendriks, 2021), where 76 participants completed 32 randomized crossing combinations of crossing conditions in 2019. The environments were all simulated with iVR and tested on simulations of an existing crossing in Rotterdam. The distractions consisted of none, visual, phone, and visual and phone combined distraction, and were tested both with and without child accompaniment, with variated traffic density. Another variable was the use of AVs. The effects of AVs on three different types of distraction have been studied little, just as the use of iVR with distractions during pedestrian crossing.

Two techniques used in this study for prediction are Restricted Boltzmann Machine (RBM) and XGBoost. Little research has been done in terms of using RBMs to classify pedestrian crossing. XGBoost has also scarcely been used for this. At last, for analyzing the effects of the variables on waiting time the Cox Proportional-Hazards model, a regression model, was used. For analysis of pedestrian behavior, Cox models have been used extensively for analyzing waiting times and risk violations (Hamed, 2001).

LITERATURE REVIEW

This section gives an overview of the existing literature on waiting time, the impact of distractions and stress on waiting time, autonomous vehicles, and immersive virtual reality as a tool.

Waiting Time

Pedestrian behavior has been studied and modeled in many studies, mostly to improve pedestrian safety (Hamed, 2001; Deb, Carruth, Sween, Strawderman, & Garrison, 2017) and pedestrian-AV interaction (Rodríguez Palmeiro, van der Kint, Vissers, Farah, de Winter, & Hagenzieker, 2018; Kalatian & Farooq, 2021), which can help improve AVs and trust in AVs. Looking at current literature, most studies use waiting time as an independent variable as part of bigger analyses. Kalatian et al. and Kalatian & Farooq focused on waiting time and found that decreased safety, slower traffic, and higher age positively impacted waiting time, whereas crossing speeds had negative impacts (Kalatian & Farooq, 2019; Kalatian et al., 2020). The impact of distractions differed, of which details will be discussed below.

Research is also divided on the type of intersections: signalized and unsignalized, depending on whether crossing is regulated. This influences pedestrian behavior as well, with the biggest differences being fewer conflicts between drivers and pedestrians at signalized intersections, pedestrians having higher situational awareness on signalized intersections and, therefore, have higher chances to avoid collisions (Hatfield & Murphy, 2007; Aghabayk, Esmailpour, Jafari, & Shiwakoti, 2021). This study only focuses on unsignalized intersections.

Crossing Distractions

Unsignalized crossings require more situational awareness (Aghabayk et al., 2021). Pedestrians need to pay attention to many environmental factors to determine when to cross. Decisions at intersections need to be made quickly because of the dynamic environment, which can be affected by several distractions either from the environment or self-imposed by pedestrians (Tapiro et al., 2018).

Visual and auditory distractions, like billboards, dense traffic, and noise, are a part of environmental distractions found in urban areas and linked to pedestrian injuries (Dissanayake, Aryaija, & Wedagama, 2009). Auditory distractions have less impact on pedestrian behavior than visual distractions but lead to unsafe crossing (Tapiro et al., 2018). Environments with an excess of visual distractions, called 'visual clutter', are particularly distracting, leading to unsafely crossing (Rosenholtz, Li, & Nakano, 2007; Tapiro et al., 2018). As the number of distractors went up, impacts also increased (Tapiro, Oron-Gilad, & Parmet, 2020). Visual and auditory distractions increase waiting time (Tapiro et al., 2018). However, most studies researching these distractions and waiting time focus on phone distractions.

Self-imposed distractions mostly include phones. Because smartphones utilize cognitive action, they are considered separately from environmental distractions (Hatfield & Murphy, 2007; Nasar, Hecht, & Wener, 2008; Schwebel, Stavrinos, Byington, Davis, O'Neal, & de Jong, 2012). Research focusing on mobile phones as distractions during crossing has broadened from holding phone conversations to playing games. Pedestrians using phones are less likely to notice activities around them and exhibit more risky behavior

(Antić et al., 2016). Different phone activities have different impacts, with more cognitively demanding activities having bigger impact (Antić et al., 2016). Few have studied the effects of phone distractions on waiting time. Kalatian & Farooq and Kalatian et al. found that phone usage decreased waiting time (Kalatian & Farooq, 2019; Kalatian et al., 2020). However, this could be mitigated by placing safety LED lights at intersections.

The third and last category of distractors is accompaniment. Several studies have analyzed the effects of crossing with other people in comparison to crossing alone and found that adult pairs are more likely to choose opportunities with bigger crossing gaps compared to individuals, and adolescent pairs cross less safely than adult pairs (O'Neal et al., 2019). Adult-child pairs have also been studied (Zeedyk & Kelly, 2003; Rosenbloom, Ben-Eliyahu, & Nemrodov, 2008). Adults accompanied by children were more likely to exhibit safe crossing behavior (Zeedyk & Kelly, 2003; Arman et al., 2019). Children accompanied by an adult relied on the adult when crossing together (Rosenbloom et al., 2008; O'Neal et al., 2019). The effect of children's accompaniment on adults has not been studied extensively.

Stress

Stress is in the current study measured by electrodermal activity (EDA), which is found to be accurate for measuring stress (Setz, Arnrich, Schumm, La Marca, Troster, & Ehlert, 2010). Big stressors appear to have significant effects on the risk for traffic accidents (SELZER & VINOKUR, 1974). Stress levels also change based on the environment. Also, the impact of AVs and traditional cars on stress was measured by (Rodríguez Palmeiro et al., 2018), who found no statistically significant difference in stress between the two conditions. Pedestrians with lower stress levels exhibit safer crossing behavior (Zheng et al., 2017). However, it is unknown how aforementioned distractions impact stress on pedestrians.

Autonomous Vehicles

With expectations of AVs integrating into society, many studies have measured AVs' impact on society regarding societal, socioeconomic, sustainable, ethical, and trust changes. It is believed AVs will improve safety, reduce congestion, and improve mobility (Millard-Ball, 2016), but they could also increase travel and with that carbon emissions, and system failures (Childress, Nichols, Charlton, & Coe, 2015).

Current research on AVs concerning pedestrians focuses on different topics. It explores the effectiveness of current technology and future advancements, analyzes interactions between pedestrians and AVs, and measures sentiments regarding AVs. The latter two are necessary for increasing the positive impact of AVs on society.

Currently, pedestrian-driver interactions are based on body language cues (Mirnig, Perterer, Stollnberger, & Tscheligi, 2017), which is expected to decrease in pedestrian-AV interactions. Thus, studies are researching alternative methods of communication, like visual cues displayed on the car (Mirnig et al., 2017). To predict the actions of pedestrians during AV-interaction, studies use game theory approaches. These models suggest pedestrians will most likely behave with nonliability because of the risk-averse nature of AVs (Millard-Ball, 2016).

For the acceptance of AVs for good integration into society, research has been done to capture sentiments regarding AVs and reactions in interactions with AVs. People are fascinated by AVs and consider them low-risk, but they are also skeptical, especially regarding safety (Häuslschmid, von Bülow, Pfleging, & Butz, 2017; Hulse, Xie, & Galea, 2018). Females were more likely to see AVs as riskier than males (Hulse et al., 2018). Although, compared to traditional vehicles, participants' reactions did not seem significantly different (Rodríguez Palmeiro et al., 2018).

Considering waiting times, Kalatian and Farooq showed that pedestrians have longer waiting times with AVs (Kalatian & Farooq, 2021). Other studies on waiting time with AVs are scarce.

Immersive Virtual Reality (iVR)

iVR as a tool to study pedestrian behavior is gaining ground, because it allows users to immerse themselves completely in virtual environments and their elements, and lets users interact with them (Deb et al., 2017). Researchers gain the freedom to simulate realistic environments from within a room with minimal risk for participants at a reduced cost (Deb, S., et al, 2017). When tested for the validity of iVR to the real world, no significant differences were found when comparing measures obtained through VR and real-life measures (Deb et al., 2017; Deb, Strawderman, & Carruth, 2018). Advancements push iVR to become more realistic in simulating the real world (Sobhani & Farooq, 2018).
In pedestrian research, iVR is used for testing its effectiveness for teaching pedestrian safety and understanding pedestrian crossing choices and interactions between pedestrians and (automated) vehicles. The impact of distractions on pedestrians was also studied with iVR systems (Schwebel et al., 2012; Sobhani & Farooq, 2018; Kalatian et al., 2020). However, research on this impact and AVs together is scarce. Kalatian & Farooq did a similar study, but it did not include distractors (Kalatian & Farooq, 2019).

Model Use for Analysis

Two techniques used in this study for prediction are Restricted Boltzmann Machine (RBM) and XGBoost. RBMs are a form of Boltzmann machines that use a layer of hidden binary units to model probabilities over a set of inputs. One common application in pedestrian research is pedestrian recognition, used to improve automated vehicles, and other detection research (Creusot & Munawar, 2015). Little other research was done with RBMs to classify pedestrian crossing behavior.
XGBoost is a machine learning system for gradient tree boosting (Chen & Guestrin, 2016), which is used for classifying pedestrian detection and recognizing factors influencing crash types. Otherwise, little research in pedestrian crossing used XGBoost, except for classifying early pedestrian movement for detecting intentions towards approaching vehicles (Botache, Dandan, Bieshaar, & Sick, 2019). However, no studies were found using XGBoost to predict waiting time and analyze variables of pedestrian crossing.
At last, the Cox Proportional-Hazards model is a regression model that analyzes the association between the survival time and other predictor variables, or in this study, the waiting time. For the analysis of pedestrian behavior, Cox models were used extensively for analyzing waiting times and risk violations (Hamed, 2001; Kalatian & Farooq, 2019, 2021). It was found that mostly age, trip purpose, and safety awareness influenced waiting time (Kalatian & Farooq, 2021).

METHODOLOGY

Firstly, the data collection method will be described. Then, the model structures will be explained.

Survey Design

The dataset used was collected in (Hendriks, 2021) and consisted of the iVR system and a survey. Examples of the iVR system and its simulations are shown in **Figures 1 through 8**.
The iVR system (**Figure 1 & 2**) was used for assessments of crossing performance within the VR. The system consisted of the simulation environment of an existing intersection in Rotterdam modified (**Figure**

3), the traffic simulation based on real traffic data that was collected (**Figure 4**), and the EDA component, measuring EDA through a wristband.

During the experiments, participants were trained for familiarization, and a baseline was recorded. The actual session was divided into eight crossing conditions and four traffic scenarios. The crossing conditions consisted of 1. no distraction (**Figure 5**), 2. visual distraction (**Figure 6**), 3. phone distraction (**Figure 7**), 4. phone and visual distraction combined, 5. accompanied crossing (**Figure 8**), 6. accompanied crossing plus visual distraction, 7. accompanied crossing plus phone distraction, and 8. accompanied crossing plus phone and visual distraction. The traffic scenarios consisted of 1. low traffic volume (1140 cars/hour), 2. medium traffic volume (1380 cars/hour), 3. medium-high traffic volume (1680 cars/hour), and 4. high traffic volume (2220 cars/hour). The combinations of the conditions were generated randomly. Each trial was designed to last a maximum of 60 seconds.

Alongside the experiment, a survey was given to the participants to collect their demographics.

FIGURE 1 – VIVE HTC PRO (HTC Vive Pro Eye - Coolblue, n.d.) **FIGURE 2 – iVR DEMONSTRATION (Hendriks, B, 2021)**

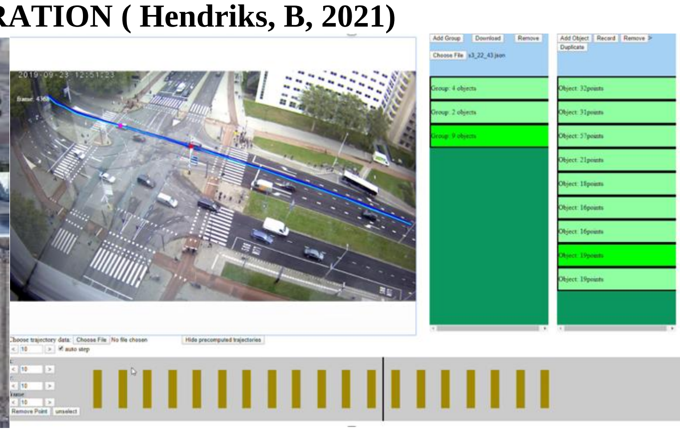

FIGURE 3 – THE SIMPLIFIED INTERSECTION BASED ON GOOGLE MAPS (Maps, 2021) **FIGURE 4 – TRAFFIC DATA COLLECTION (Hendriks, B, 2021)**

FIGURE 5 – NO DISTRACTION (Hendriks, B, 2021) **FIGURE 6 – VISUAL DISTRACTION (Hendriks, B, 2021)**

FIGURE 7 – PHONE DISTRACTION (Hendriks, B, 2021) **FIGURE 8 – ACCOMPANIMENT (Hendriks, B, 2021)**

Restricted Boltzmann Machine Model Structure

The RBM is a variation on Boltzmann machines, an unsupervised network of binary units, where input goes from the visible layer through one or several layers of hidden units. For each RBM, the energy function is calculated as follows (**Equation 1**) (Chu, Zhao, Zou, Xu, Han, & Zhao, 2018):

$$E(v,h) = -\sum_{i=1}^{m} b_i v_i - \sum_{j=1}^{n} a_j h_j - \sum_{i=1}^{m}\sum_{j=1}^{n} v_i w_{i,j} h_j \qquad (1)$$

where:
m and *n* refer to size *m x n* of weights matrix,
v_i and h_j are binary states at visible neuron *i* and hidden neuron *j*, respectively,
b_i and a_j are corresponding biases of neurons,
w_{ij} is connection weight between unit *j* and unit *i*.
Then, parameters of the RBM are trained by maximizing log-likelihood function and from that follows the final learning rule of connection weights (**Equation 2**) (Chu et al., 2018):

$$\Delta w_{ij} = \eta(E_{data}[v_i h_i] - E_{model}[v_i h_i]) \qquad (2)$$

where E_{data} and E_{model} are the expectation under the distribution of the training dataset and the model.

Regularized Gradient Boosting Tree Model Structure

The XGBoost algorithm is a machine learning algorithm using decision trees and gradient boosting, which combines several weak links within trees to get a stronger model. XGBoost minimizes the following regularized objective (**Equation 3**) (Chen & Guestrin, 2016):

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \qquad (3)$$

where:
l is loss function measuring differences between prediction $\hat{y}_i$ and target y_i for each i^{th} leaf,
Ω penalizes the complexity of the model and smooths over final weights of each independent tree structure f_k to avoid overfitting.

Based on the previous formula, we calculate the optimal value at step t as follows (**Equation 4**)(Chen & Guestrin, 2016):

$$\tilde{\mathcal{L}}^{(t)}(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\in I_j} g_i\right)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma T \qquad (4)$$

where:
T is the number of leaves in the tree,
g and h are functions derived from first and second-order gradient statistics of loss function,
I_j refers to bracket $i|q(x_i) = j$ bracket as the instance set of leaf j,
γT and λ are derived from $\Omega(f_k)$.

Cox Proportional-Hazards Model

The model is expressed with a hazard function of the following form (**Equation 5**) (Cox, 1972):

$$h(t) = h_0(t) * \exp(\beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta x_{ip}) = h_0(t) * \exp(\beta x_i) \qquad (5)$$

where:
t is survival time,
$h(t)$ is hazard function, the likelihood of an event at time t,
h_0 is baseline hazard, the value of hazard function if there are no covariates,
$\beta_1, \beta_2, \ldots, \beta_i$ are coefficients that measure the impacts of the covariate.

Estimation of β is done by maximizing log-partial likelihood function (**Equation 6**) (Cox, 1972):

$$\ell(\beta) = \sum_{i=1}^{n}\left[\beta x_i - \log\left(\sum_{\ell\in R_i} \exp\right)\right] \qquad (6)$$

where:
n is the number of individuals I,
R_i represents risk set, set of risk scores βx_i.

$exp(\beta_i)$ are the hazard ratios. β_i having a value of greater than zero indicates that as the covariate increases, the hazard increases, which means that the waiting time decreases.

DATA

In this section, variables used in the study will be discussed and a descriptive and sensitivity analysis will be performed.

Variables

The analysis focused on variables from (Hendriks, 2021). These are divided into five categories: crossing variables, distraction variables, safety measures, physiological measures, and socio-demographic variables. The first four categories were measured during the experiment, and the socio-demographic variables were obtained from the survey.

The crossing variables consist of waiting time duration, crossing time duration, crossing speed, initial speed, and the simulated traffic volume. The distraction variables consist of the following variables, measured while waiting and crossing: percentage of time spent looking at one of the distractors (phone, visual distraction, child), the percentage of time spent looking at traffic, the percentage of time spent looking at different directions, and the number of mazes solved. The safety measures consist of the mean post-encroachment time (PET; the time difference between the pedestrian departing and a vehicle arriving at a collision point), the initial walking speed, and the mean acceleration and deceleration. The physiological measure used is the EDA. The socio-demographic variables consist of age, gender, education, income, prior experience with VR, the main mode of transportation, and general walking behavior.

Descriptive analysis

76 volunteers participated in total. The mean waiting time is 16.15 seconds, the median is 12.47 seconds, and the standard deviation is 8.80 seconds. In **Table 1**, waiting time is compared with distraction scenarios and the presence of AVs. In general, waiting time seems to be lower in situations with than in situations without AVs. Waiting time also seems to increase with the number of distractions, especially in general and with AVs. In **Table 2**, waiting time is compared with some other variables. Safety, low acceleration, increased initial walking speed without AVs, and female has positive effects on waiting time, while age of 25-65 has lower waiting time.

Sensitivity analysis

The variables age, initial walking speed, traffic volume, and gender are tested for interaction with different distraction conditions, which can be seen in **Figures 9 through 12**.

TABLE 1 – AVERAGE WAITING TIME FOR EACH DISTRACTING SCENARIO AND AV SETTING

			Waiting time *(s)*		
			General	*No AV*	*AV*
Distr	Not accompanied	*No distraction*	14.57	17.50	12.32

		Visual distraction	14.85	18.13	12.32
		Phone distraction	15.15	17.69	13.27
		Phone and visual distraction	15.76	18.76	13.53
	Accompanied	*No distraction*	16.40	19.09	14.27
		Visual distraction	16.26	18.69	14.36
		Phone distraction	18.11	20.87	15.94
		Phone and visual distraction	17.92	21.01	15.21

TABLE 2 – AVERAGE WAITING TIME FOR SOME SAFETY AND SOCIO-DEMOGRAPHIC VARIABLES, WITH AV COMPARISON

			Waiting time (s)		
			General	*No AV*	*AV*
Safety	PET	< 1.5 s	15.86	17.89	14.36
		1.5 – 3 s	15.75	19.66	12.38
		3 – 5 s	21.12	27.98	13.72
Crossing behavior	Initial Walking Speed	< 0.25 m/s	15.62	19.60	13.25
		0.125 – 0.25 m/s	16.34	19.17	14.19
		> 0.25 m/s	16.07	18.53	13.75
	Mean acceleration	< 0.25 m/s	24.63	26.40	22.47
		0.125 – 0.25 m/s	14.23	16.83	12.43
		> 0.25 m/s	10.33	11.54	9.56
Socio-demographics	Age	18 – 25 years	17.65	19.58	14.37
		25 – 65 years	14.58	17.64	13.31
		65+ years	17.65	19.51	15.36
	Gender	Female	16.47	19.40	13.77
		Male	15.93	18.71	13.99

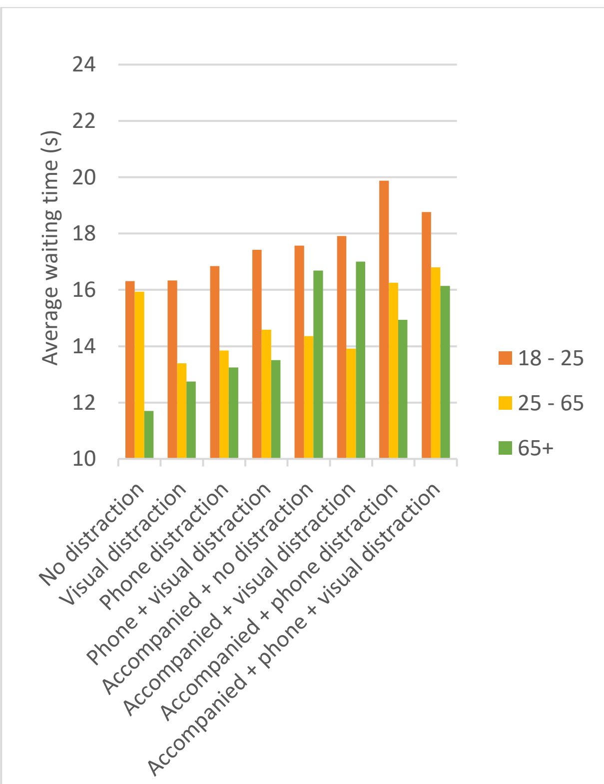

FIGURE 9 – AGE EFFECT ON WAITING TIME ACROSS CONDITIONS

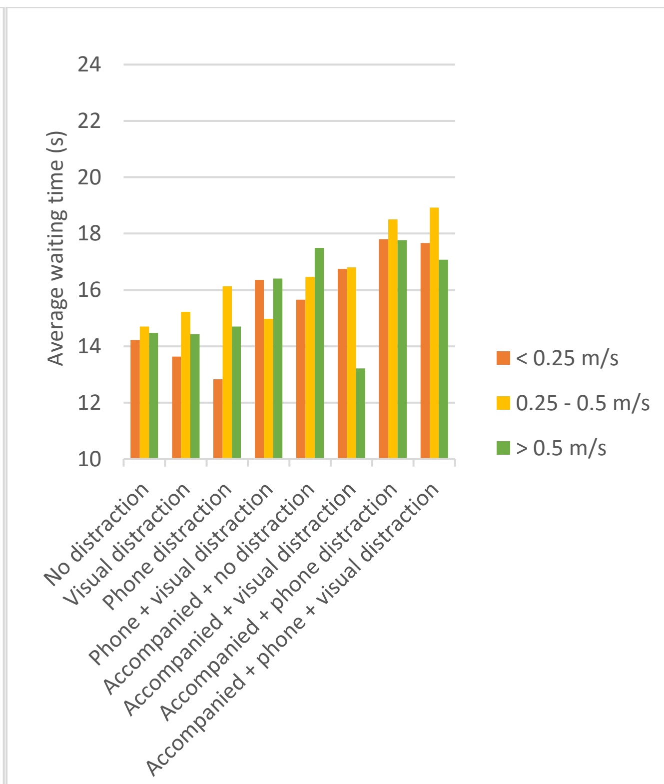

FIGURE 10 – EFFECT OF INITIAL WALKING SPEED ON WAITING TIME ACROSS CONDITIONS

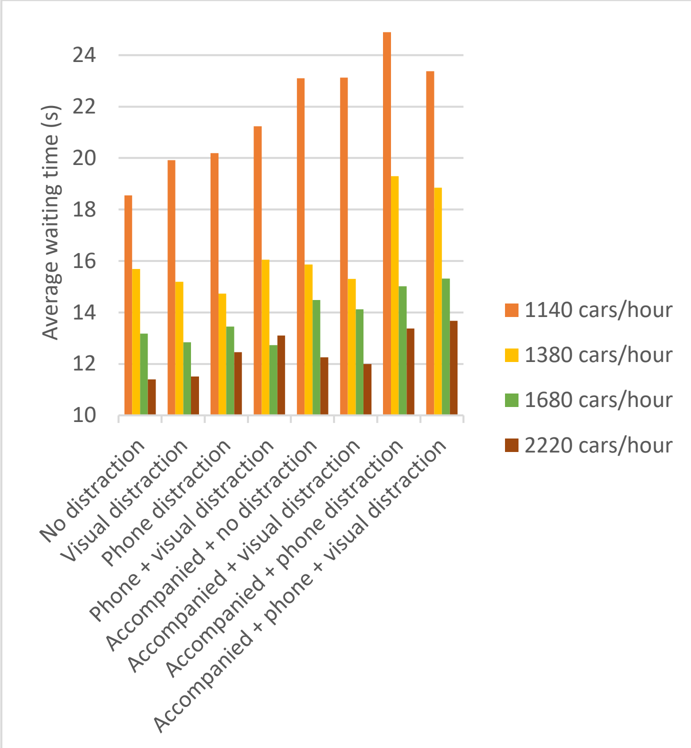

FIGURE 11 – TRAFFIC VOLUME EFFECT ON WAITING TIME ACROSS CONDITIONS

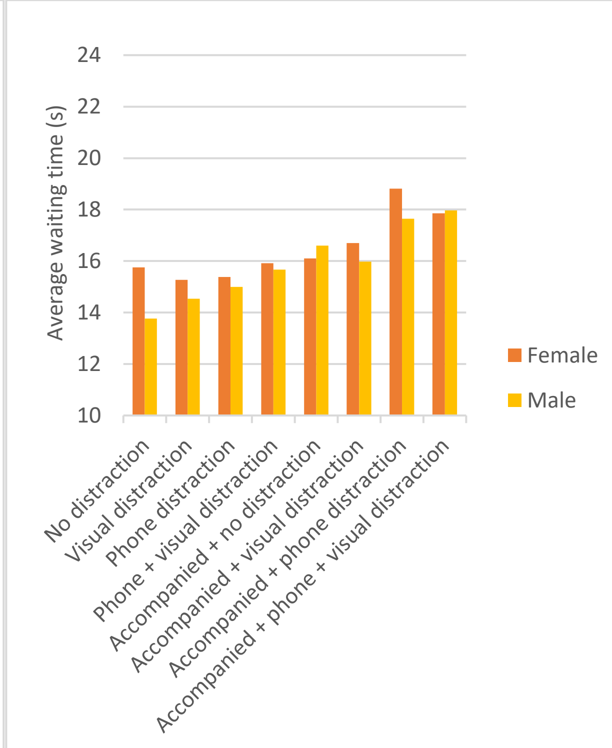

FIGURE 12 – GENDER EFFECT ON WAITING TIME ACROSS CONDITIONS

RESULTS

Firstly, RBMs and XGBoost models were tested and discussed. Then, the results of the best-performing model, XGBoost, were put into the Cox Proportional-Hazards model.

Performance

Firstly, waiting time was predicted by the RBM. Since RBMs are binary, waiting time was divided into a binary variable. The cut-off points of the two trials were at 12 and 16, the approximate median and mean of the waiting time, respectively. The accuracy of the trials was between 47% and 49%. When looking at the predictions, the fitted RBM model guessed the same prediction for the whole set, which made the RBM model unfit.
With XGBoost, the model without tuned hyperparameters produced a mean absolute error of 0.20. After several tries, the accuracy of 99% with automatically selected hyperparameters was higher than tuning manually or by Hyperopt, and XGBoost model with Random Forest incorporated.

Model Parameters

With the XGBoost model, a sample of prediction for waiting time was generated for the test set of the whole dataset. The Cox Proportional-Hazards model was created. First, highly correlated variables were removed to prevent high convergence. After that, the model was tested on the variables, firstly on interaction variables and then on pure variables, adding non-highly correlated variables before adding highly correlated one by one. Associations with a low significance (p-value > 0.25) were dropped. **Table 3** shows the results of the model with its p-value in the brackets. Non-significant effects were left out.

Distractions

When looking at distractions, there is an overall positive effect of the scenario ID on waiting time, which means that the waiting time is more likely to increase when traffic volume increases (Sobhani & Farooq, 2018). The number of solved mazes has a negative effect, meaning that waiting time is likely to decrease for every solved maze. An increased number of solved mazes means increased phone engagement and decreased likeliness to wait for traffic to stop (Hatfield & Murphy, 2007; Nasar et al., 2008).

The rest of the distraction results is divided into distractions while waiting and while crossing. While waiting, looking at kid is more likely to lower waiting time. (Zeedyk & Kelly, 2003) showed that the behavior of adults crossing with children improved in safe crossing behavior. Looking at kid shows situational awareness, which increases safety and decreases waiting time. Looking at cars and looking left negates waiting time. This could indicate that the person is more focused on traffic, which helps improve situational awareness (Aghabayk et al., 2021), a quicker estimation of crossing opportunities, and lower waiting time. Looking forward, however, is more likely to increase waiting time. This could be due to looking forward not providing enough insight into traffic, or it shows that the participant is distracted. If participants looked at visual distractions, waiting time is more likely to increase, with looking at a billboard being the most impactful visual distraction, which could be due to visual clutter (Rosenholtz et al., 2007). At last, a higher number of solved mazes lowers waiting time, like before.

While crossing, looking at visual distractions decreased waiting time, and solving mazes increased waiting time. This is the opposite of earlier outcomes, which indicates that during crossing, distractions have different impacts. Looking at visual distractions while crossing could be considered distraction enough to defer from the focus on traffic, which decreases safety waiting time (Tapiro et al., 2018). Furthermore, looking at cars increased waiting time. More specifically, if participants looked at cars more than 50%, waiting time is also likely to increase. However, if the participants looked at cars more than 50% while having a phone and visual distraction, waiting time is more likely to decrease. This could indicate the impact that distractions have on situational awareness, which influences waiting time (Aghabayk et al., 2021).

Earlier, an increase in waiting time was seen when traffic increased. This turned to be significantly true for different distractions present while crossing, which confirms (Tapiro et al., 2020), who found that children and adults missed more opportunities to cross the road when exposed to cluttered environments, which increases waiting time. These effects are in comparison with low traffic (1140 cars/hour). With 1380 cars per hour, waiting time increases with visual distraction with and without traditional cars, and in an accompanied setting with visual distraction and AVs, but is more likely to decrease with traditional cars. This could be due to nonliability behavior of pedestrians when encountering AVs (Millard-Ball, 2016). With 1680 cars per hour, distractions with visual, phone, accompanied, and phone and accompanied combined distraction provided significant increase in waiting time. These are all with traditional cars, which means that higher traffic densities increase waiting time (Kalatian & Farooq, 2021). With 2220 cars per hour, some distractions, mostly with accompaniment, with traditional cars increased waiting time significantly. However, with AVs and phone and visual distractions, waiting time is more likely to decrease. This could be due to participants being overwhelmed by traffic and distractions and therefore, behaving more assertively with AVs (Millard-Ball, 2016).

Crossing behavior

Behavior during crossing also influenced waiting time. In two settings, initial walking speed decreased waiting time compared to a low initial walking speed of ≤ 0.25 m/s. This could be due to a rushed start meaning they are more likely to cross quicker. Furthermore, in general, an increase in mean acceleration increased waiting time. This indicates rushing, which could mean that participants were not confident of crossing and waited longer for an opportunity (Hatfield & Murphy, 2007; Sobhani & Farooq, 2018). Otherwise, if participants showed an increase in mean deceleration, this indicated lower waiting time. Rapid decelerations are associated with safer crossings (Nadimi, Ragland, & Mohammadian Amiri, 2019). If participants walk slower while crossing, they will initiate crossing earlier. Despite mean acceleration showing an increase in waiting time, in two scenarios, there was a decrease in the waiting time with higher maximum acceleration: when acceleration was between 0.125 and 0.25 m/s with traditional cars and phone and visual distraction, and when maximum acceleration was more than 0.25 m/s with AVs and phone distraction, in comparison to a low maximum acceleration of < 0.125 m/s. Since phone distraction was available in both situations, this confirms earlier research, stating that phone distractions decrease safety and waiting time (Antić et al., 2016). Considering maximum deceleration between 0.75 and 1.25 m/s with AVs and visual distraction, waiting time is more likely to decrease compared to deceleration of < 0.75 m/s, in line with the general decrease of mean deceleration. However, with traditional cars and accompaniment combined with a distraction, increased deceleration between 0.75 and 1.25 m/s showed increased waiting times. This could be because children walk slower, and together with other distractions, participants are more likely to wait for opportunities with a bigger window. Lastly, increase in crossing speed, with traditional cars and accompaniment of a child, and with AVs with accompaniment, phone, and visual distractions combined, decreased waiting time, in comparison with speeds of < 0.65 m/s. This means that participants with higher speeds wait shorter before crossing, which could be explained by participants wanting to cross faster and unsafe, and therefore waiting shorter (Sobhani & Farooq, 2018).

Safety & stress

The safety measure PET turned out to have significant general effects on waiting times. Increased PET decreases waiting time. Increased PET also means safer crossing, which leads to participants being more confident in estimating safety (Zhao, Malenje, Wu, & Ma, 2020). Therefore, participants initiate crossing earlier. However, this finding does contradict some research where increased waiting times are seen as safer (Kalatian et al., 2020; Kalatian & Farooq, 2021).

In only one situation, the effect of stress turned out significant. Here, stress increased waiting time, which could be due to people having difficulties making decisions while experiencing stress (SELZER & VINOKUR, 1974). However, the significance is relatively high.

Socio-demographics

Firstly, with age, compared to the group below 25, an increase in the group 25-65 with AVs and phone and visual distraction combined is more likely to increase waiting time. This means that the older the participants, the higher their waiting time if they have distractions, and with AVs (Aghabayk et al., 2021). An increase in the 65+ group with traditional cars and accompaniment and phone distraction combined showed a decrease in waiting time. Perhaps elderly have a lower capacity to divide their attention, so they get less distracted. This is opposing current research.

Living in the Randstad also had significant impact on waiting time. Compared to participants not living in the Randstad, with the distractions of accompaniment and a phone, they showed a likely decrease in waiting time. Living in cities leads to higher exposure of situations as simulated (Tapiro et al., 2020). Since those participants are already familiar, they can more confidently initiate crossing.

Participants with Western ethnicity, with AVs, had increased waiting times compared to participants of non-Western ethnicity. With accompaniment, visual distraction, and traditional cars, Western participants had lower waiting times. This could be explained by intersections being more familiar to Western participants than non-Western participants (Jiang, Wang, Bengler, & Guo, 2015).

Participants who used VR before had higher waiting times with AVs, accompaniment, and phone distraction than participants who did not use VR. Waiting time was more likely to increase. Since participants who have used VR are more comfortable with the technology (Deb et al., 2018), they can make safer decisions, which involves higher waiting times.

Household composition had negative effects on waiting time. With all distractions and AVs, participants in households with two adults had lower waiting times compared to participants in households with one adult. Participants with three adults in the household and with traditional cars had lower waiting times when accompanied with and without phone distraction. Waiting time was more likely to decrease.

Having three cars in a household in a setting with traditional cars, accompaniment, and visual distraction decreased the waiting time compared to participants of households with no cars. Car users could feel safer in crossings than other users. However, in settings with AVs present, situations with only a visual distraction and situations with all distractions present had an increased waiting time, which could be due to lower trust in AVs by drivers.

Having a bike decreased waiting time in general and with visual distraction, where visual distraction had more impact. Since bikers participate in traffic, they could be more comfortable with the intersection and need less time to wait before crossing.

Participants who reported using phones while crossing had lower waiting times in general than participants who reported not using their phones. Since they are more familiar with the situation, they are more comfortable crossing and need less time to initiate crossing. However, with all distractions, phone users had higher waiting times compared to non-users. Since they are used to looking at their phone, users could be looking more at their phones than non-users and be more distracted by them.

No table of figures entries found.			Vehicle type		Distractions			Distractions and accompaniment			
					Visual	**Phone**	**Phone and visual**	**Accompanied with child**	**Accompanied with child + Visual distraction**	**Accompanied with child + Phone distraction**	**Accompanied with child + phone and visual distraction**
Distractions	**Scenario ID**	*Traffic conditions*	General	0.24 (<0.005)							
	Number of mazes solved	*General*	General	-0.13 (<0.005)							
Waiting	**Looking at kid**	*General*	General	-0.62 (0.24)							
	Looking at car	*General*	General	-0.55 (<0.005)							
	Looking at visual distraction	*General*	General	1.68 (0.10)							
	Looking at billboard	*General*	General	4.11 (0.03)							
	Looking forward	*General*	General	0.80 (0.08)							
	Looking left	*General*	General	-0.69 (0.13)							
	Number of solved mazes	*General*	General	-0.16 (<0.005)							
Crossing	**Looking at visual distraction**	*General*	General	-1.50 (0.11)							
	Number of solved mazes	*General*	General	0.20 (0.05)							
	Looking at car	*General*	General	1.16 (<0.005)							
		> 50%	General	0.23 (0.15)			-0.63 (0.13)				
	Traffic	*1380 cars/hour*	General		0.64 (0.05)				-0.35 (0.22)		
			AV		2.07 (<0.005)				0.55 (0.13)		
		1680 cars/hour	General		0.49 (0.10)	0.39 (0.10)		0.32 (0.18)		0.53 (0.06)	
		2220 cars/hour	General		0.60 (0.02)			0.74 (0.01)	0.54 (0.06)	0.32 (0.24)	
			AV				-0.83 (0.01)				
	Initial walking speed	*>0.25 & <=0.5 m/s*	General					-0.24 (0.24)			
		>0.5 m/s	AV							-0.48 (0.07)	
	Mean acceleration	-	General	5.91 (<0.005)							
	Maximum acceleration	*>0.125 & <=0.25 m/s*	General				-0.38 (0.04)				
		>0.25 m/s	AV			-0.80 (0.03)					
	Mean deceleration		General	-2.49 (<0.005)							
	Maximum deceleration	*>0.75 & <=1.25 m/s*	General						0.46 (0.16)	0.56 (0.06)	
			AV		-0.74 (0.07)						
	Speed	*> 0.85 m/s*	General					-0.51 (0.05)			
			AV								-0.58 (0.02)
Safety	**PET**		General	-0.35 (<0.005)							
Stress	**Stress levels**	*Experienced stress*	General				0.28 (0.18)				
Socio-demographics	**Age**	*25 - 65*	AV				0.39 (0.13)				
		65+	General							-0.54 (0.09)	
	Hometown	*Randstad*	General							-0.32 (0.07)	
	Ethnicity	*Western*	General						-0.80 (<0.005)		
			AV	0.23 (0.03)							
	Used VR before	*Yes*	AV							0.48 (0.06)	
	Number of adults in household	*2 adults*	General								-0.70 (< 0.005)
		3 adults	General					-0.32 (0.19)		-0.35 (0.14)	
	Number of cars in household	*>1 car*	General						-0.56 (0.03)		
			AV		1.04 (0.02)						0.78 (0.03)
	Have bike	*Yes*	General	-0.51 (<0.005)	-0.54 (<0.005)						
	Use phone while crossing	*Yes*	General	-0.29 (<0.005)							0.73 (< 0.005)

	Transportation	*Main mode is car*	AV			0.64 (0.06)	0.60 (0.07)				
		Walk to school	General		-0.36 (0.20)						-0.72 (0.03)
			AV	0.41 (0.01)					0.70 (0.08)		
		Walk for groceries	General	0.26 (0.03)							
			AV	0.39 (<0.005)							

TABLE 3 – FINAL RESULTS OF THE COX PROPORTIONAL-HAZARDS MODEL

At last, the main mode of transportation had an impact on waiting time. Participants with cars compared to participants with a bike had higher waiting times with AVs and phone distraction, and phone and visual combined distraction (Kalatian & Farooq, 2019). They showed increased waiting time, which could be explained by lower trust in AVs by drivers. Participants who reported walking to school had lower waiting times with traditional cars and all distractions. With AVs, they had increased waiting time, with a bigger impact with accompaniment and visual distraction combined. The participants walking for groceries reported increased waiting time with AVs.

CONCLUSION

This study aimed to test the influence of different distractors, vehicle types, and stress on pedestrian waiting time at unsignalized intersections through immersive virtual reality. Data were analyzed using RBM and XGBoost, and XGBoost was used to predict waiting time. Associations between predicted waiting time and other variables were analyzed using the Cox Proportional-Hazards model.

The distractors with the biggest impact were looking at visual distractions and looking at billboards while waiting, which increased waiting time, complying with (Rosenholtz et al., 2007). Increased traffic and looking forward while waiting also increased waiting time, possibly indicating participants experiencing visual clutter and limited situational awareness (Aghabayk et al., 2021). Variables decreasing waiting time were the number of solved mazes in general, looking at kid, looking left, and looking at cars. The number of solved mazes is linked to unsafe crossing and lower waiting time (Kalatian et al., 2020). An increase in the other factors could lead to higher situational awareness, which also lowers waiting time. Furthermore, mean acceleration and mean deceleration had the biggest impact on waiting time, acceleration increasing waiting time and deceleration decreasing it (Nadimi et al., 2019). However, with distractions, acceleration decreases waiting time. Longer waiting time and acceleration could indicate participants not being confident to cross and rushing (Hatfield & Murphy, 2007; Sobhani & Farooq, 2018). Further, increased safety leads to lower waiting times and increased stress leads to higher waiting times. Lastly, considering socio-demographic variables, the age group 25-65, Western ethnicity, having used VR before, having more than one car in the household, a car being the main mode of transportation, and walking to school (with AVs) or for groceries, all increased waiting time. Older participants, having higher numbers of adults in the household, having a bike, and walking to school (with traditional cars) decreased waiting time. Remarkably, the most significant effects were seen with traditional cars, which could be due to different sentiments about AVs (Hulse et al., 2018).

There are a few limitations. Firstly, the experiment could be done with different factors included, like different road landscapes, and including perspectives of other road users. Also, future studies could be studied with bigger sample sizes and in different locations for better generalization.

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