HAL2019-01: Development and Evaluation of Vehicle to Pedestrian (V2P) Safety Interventions

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Executive Summary

Pedestrian deaths are on the rise with 6,227 estimated for 2018, the highest since 1990. Distractions such as walking while looking at electronic devices are the third leading cause of fatalities and one study has shown that injuries from distracted walking have increased 81% since 2005. The introduction of self-driving cars could further complicate this problem as illustrated by the death of a pedestrian caused by an Uber self-driving car in 2018. To examine how well an electronic alerting device installed on a smartphone could prevent distracted pedestrians from making unsafe or risky crossings, an experiment was conducted in an actual controlled field setting. Using a smartphone with a remotely controlled alerting systems, thirty participants performed thirty crossings each while walking and playing a game on the smartphone. In addition to just-in-time alerts, two-thirds of participants were presented with early and late alerts which constituted 80% and 90% alarm reliabilities.

Out of 900 crossing events, 20% of crossings were risky or unsafe, with the bulk of these happening when a smartphone-based alert was given at a time that allowed participants to have just enough time to safely cross. When the alert was late, the percentage of unsafe crossings were just 2% of the total number of crossings, but 33% of all late crossing attempts. More than 18% of participants exhibited underestimation bias and thought the car was farther away than it really was. These numbers align with other observational research studies looking at typical pedestrian behaviors.

Half of the participants were Americans and half were Asians, and the Asians statistically had the highest number of risky crossings in the presence of oncoming cars when compared to Americans. Even though Asians as a group were more likely to attempt risky crossings while engaged in distracted walking, they also trusted the alert less when it generated early and late warnings. A machine learning decision tree model illustrated that the best odds for safe crossings were those people who scored lower than average on a neuroticism scale of a personality test and tended to stop more than 2.25’ from the road’s edge. Asians with higher than average neuroticism scores who stopped less than 1.75’ from the road were twice as likely to put themselves in an unsafe crossing situation.

These results suggest that culture plays an important role in the use of technological interventions meant to promote positive behaviors and that a solution effective in one setting may not generalize to other cultures. Moreover, technology interventions like smartphone-based alerts do not produce substantially safer pedestrian behaviors than those observed in populations without such tools. While the subject pool was small in this study and more research is needed in larger populations, this research suggests that that there may design criteria that can be elucidated from such use of machine learning classification methods in concert with controlled experiments.

Introduction

Pedestrian deaths have steadily risen in the past two decades with approximately 6000 people killed annually in 2016 and 2017 (National Center for Statistics and Analysis 2018). Recent estimates for 2018 pedestrian deaths indicate the highest number to date since 1990, at 6,227, which is an increase of four percent over 2017 (Retting 2019). The top three causes of these fatalities are speeding, failing to yield, and distractions such as electronic devices (Swanson, Yanagisawa et al. 2016, Schaper 2017). One study has shown that injuries from distracted walking have increased 81% since 2005, with those 16-25 years old affected the most (Nasar and Troye 2013). In one observational study in Seattle, approximately 30% of all pedestrians observed performed a distracting activity while crossing (Thompson, Rivara et al. 2013). The introduction of self-driving cars could further complicate this problem as the death of a pedestrian caused by an Uber self-driving car in 2018 (Laris 2018) illustrates the difficulties these cars have in sensing people outside the car.

With recent advances in electronics, car manufacturers are developing active impact protections for pedestrians to lessen the severity of impact such as hoods that raise up to prevent head injury and external airbags. However, preventing such collisions is preferable and to that end, several researchers have proposed developing a communication network that would alert a pedestrian to one or more oncoming cars. Such systems could take the form of a vehicle-to-pedestrian (V2P) alerting system or even an infrastructure-to-pedestrian alerting system where either the vehicle or a camera mounted on a streetlight, for example, could communicate directly through a smart phone with both visual and audio cues.

Several research groups are developing V2P systems that allow cars to directly communicate their presence to pedestrians or vice versa (Bagheri, Siekkinen et al. 2014, Bai and Miucic 2018). Other researchers have hypothesized that adding sensors to infrastructure at intersections can be used to communicate with smartphones of distracted pedestrians (Schewbel 2018). Yet another group of researchers has proposed alerting distracted users of unsafe conditions through smartphone cameras (Wang, Cardone et al. 2012).

While such devices could, in theory, help to mitigate pedestrian accidents and fatalities, whether such benefits can be achieved in practice are less clear. Research has shown people often tend to ignore emergency alerts from their mobile phones (Kar and Cochran 2016). Moreover, alert fatigue, which occurs when people are desensitized to frequent alerts, routinely occurs in safety-critical settings such as healthcare (Ancker, Edwards et al. 2017) and aviation (Wald 2010). Drivers of cars have shown a propensity to mistrust alarms when there are too many false alarms (Zabyshny and Ragland 2003). So, it is likely that pedestrian alerting systems embedded in either infrastructure or mobile devices would also be ignored. Indeed, preliminary pedestrian research has shown this to be the case (Rahimian, O'Neal et al. 2018).

Given that alerting systems are not perfect, especially when detecting moving vehicles at short distances, it is not clear if a smartphone alert would be helpful for distracted pedestrians and how the degree of reliability of such V2P systems could influence pedestrian adoption. To this end, an experiment was conducted in an actual controlled field setting with pedestrian participants approaching a road crossing while performing a secondary data entry task on a smartphone, detailed in the next section.

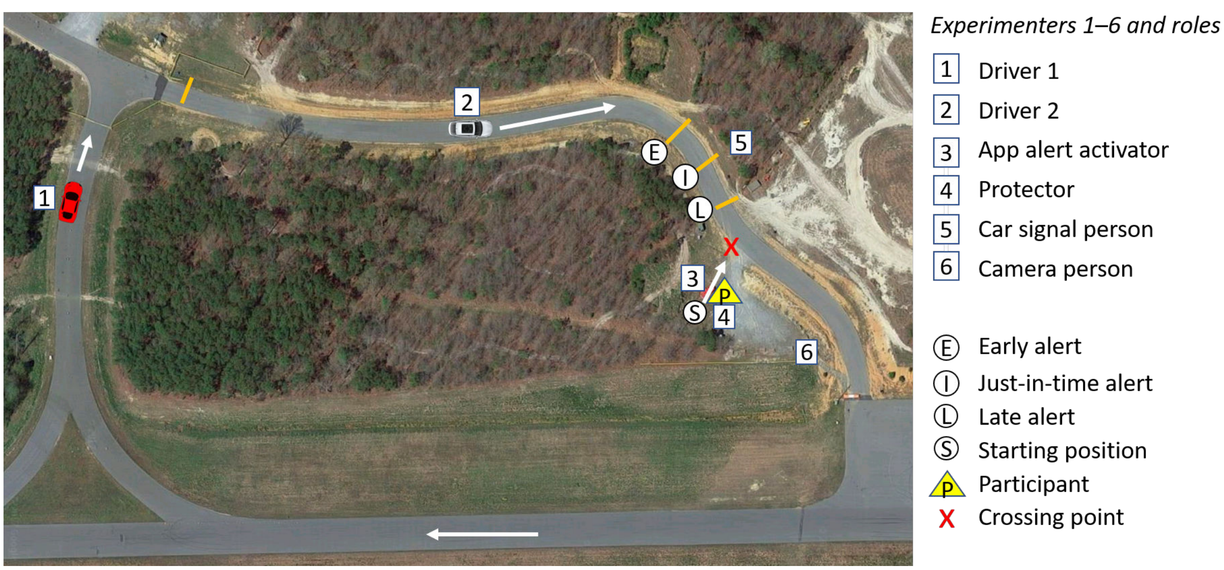

Figure 1: The experimental roadway at the North Carolina Center for Automotive Research. The intended crossing point for each pedestrian is marked with an X, and the position of the car for the early, just-in-time, and late alerts are marked with E, I, and L respectively. The positions of the support team are also marked in the legend.

Method

Participants

Thirty participants (18 male, 12 female) between the ages of 19 and 57 yrs (Mean (M)=27.1 yrs, Standard Deviation (SD) = 7.7 yrs) were recruited through listserves and flyers in the local Garysburg, NC area as well as the Raleigh-Durham metro area. Half of the participants were US citizens and half were from Asia (9 China, 5 India, 1 Saudi Arabia). There were 10 American males, 5 females and 8 Asian males, 7 females. They were paid $25 for their effort. In terms of texting on their cell phones while walking, 70% reported that they occasionally or frequently engaged in this behavior, and 37% reported they would text while crossing a street. All participants had 20/20 or corrected to normal vision and no mobility impairments

Test Environment

In order to determine how different reliabilities of smartphone alerts influenced pedestrian crossing decisions when an oncoming car was detected, we elected to design and run a controlled experiment in an actual outdoor setting, the first reported experiment of its kind. Most pedestrian studies are observational or self-report, or a combination, primarily due to the difficulties in controlling both vehicle and foot traffic (e.g., Papadimitriou, Lassarre et al. 2016). Self-reports of pedestrian behavior have been shown to be biased towards positive behaviors such as traffic rule compliance (Deba, Strawderman et al. 2017) so it is often difficult to capture realistic behaviors.

Some pedestrian studies have used immersive simulators (e.g., (Feldstein, Dietrich et al. 2016, Rahimian, O'Neal et al. 2018) to simulate pedestrian crossings, however, it is difficult to generalize such results to actual crossings since distance estimation in such environments consistently underestimates real world distances (Proffitt 2006). In one study, pedestrians in a simulator collided with vehicles in 59% of trials despite a warning, suggesting such underestimation bias (Rahimian, O'Neal et al. 2018).

In order to produce the most ecologically viable results, we conducted our pedestrian crossing experiments on a controlled roadway environment closed to the public, the North Carolina Center for Automotive Research. In additional to a typical racecar track, this facility includes roads that resemble two lane roads found in typical suburban America (Figure 1). Over the two months of testing, we used two cars each day of testing to provide a potential vehicle-to-pedestrian conflict every 1-3 minutes. These cars included a green 2017 Audi A4 sedan, a white 2017 Toyota Camry SE, a white 2018 Toyota Corolla LE, a silver 2017 Toyota Corolla LE, a beige 2018 Ford Focus, and a white 2018 Hyundai Elantra.

The goal of this experiment was to specifically examine how pedestrians, who were distracted by their smart phones, behaved in a road crossing scenario when an alert of varying reliability warned them of a possible collision. To this end, we designed a smartphone app installed on a Huawei Honor 6X with Android 7.0 Nougat OS to provide an environment that replicated a texting task. Pictured in Figure 2a, we designed a simple maze game that participants would play while they walked towards the intended crossing point (C in Figure 1). Thirty mazes were generated on 12x12 grids and randomly presented for each of the 30 trials participants would experience. Participants had to determine which of the lettered paths was the shortest, and then enter then correct sequence of letters that led from the start to the goal. When the alert was triggered, the phone's interface changed to the image in Figure 2b and remained until cleared by an Experimenter. The phone played an audible alert, four rapid honks (spaced approximately .25s apart) from a 2007 Pontiac G6, recorded externally. This alert played in the earbuds worn by every participant and it also vibrated with the standard Huawei Honor alert vibration.

Procedure

Once the IRB-approved consent form was signed, participants filled in a demographic survey as well as a NEO™ Five-Factor Inventory-3 (NEO-FFI-3). The NEO-FFI-3 is a brief but comprehensive assessment of five personality domains, including neuroticism, extraversion, openness to experience,

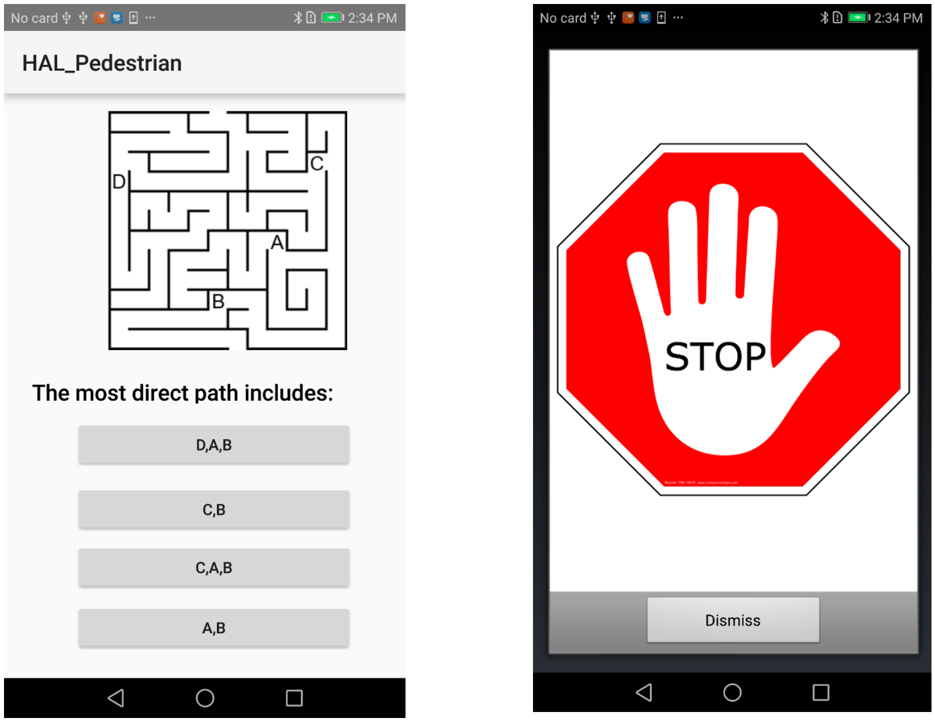

Figure 2: The Android smartphone applications: (a) maze game (left) and (b) alert warning for an oncoming car (right)

agreeableness, and conscientiousness. Previous similar research has shown that people with higher conscientiousness scores cross faster than those with lower scores (Clamann, Aubert et al. 2017).

Participants were then shown how to play the maze in Figure 2a and practiced 3-5 games to become comfortable with walking and playing the maze. Then each participant's starting point S was determined by having them walk and play the maze such that the alert occurred ~2 ft from the edge of the road (the X in Figure 1). The starting distance varied per subject and generally took two practice trials to determine. The general walking path area was outlined with cones and safety tape to ensure participants did not substantially veer from the intended path. In addition, they were always followed by the Protector to ensure their safety (Box 4 in Figure1), and two cones were set up at the road's edge to ensure participants would not step into the roadway (Figure 3).

Figure 3: A pedestrian walking towards the road, looking down at a smartphone. Participants were prevented from walking into the road by the cones and following experimenter.

Thus, for each trial, a participant would start somewhere in the vicinity of point S (Figure 1) and then walk towards the road as depicted in Figure 3 while playing the maze. In most trials, the alert was set to trigger at Point C in Figure 1 when the car was 185ft away, which gave the participant a 5s gap to cross the road (J in Figure 1). This just-in-time/distance was selected given that a healthy adult pedestrian can cross a single lane of traffic in ~2.7s (Federal Highway Administration 2012), coupled with the fact that texting on a phone increased crossing time by

1.87 additional seconds in a large-scale pedestrian observation study (Thompson, Rivara et al. 2013).

The cars held a constant speed of 25 mph when in the vicinity of the pedestrian using cruise control, and the drivers were in radio contact with each other and with the other safety monitors on the track, marked in Figure 1. Three safety personnel were always on the track. Figure 1 depicts an additional monitor located at Point 5, who signaled the car was approaching the curve and the person who activated the alarm in a wizard-of oz style to ensure correct timing for the early, just-in-time, and late alerts, the App Alert Activator, was located at position 3.

Experiment Design

Participants were assigned to one of three reliability conditions, which were 80%, 90%, or 100% alert reliability. These levels were selected since previous related research has indicated human trust is sensitive to these reliability levels (Ross, Szalma et al. 2008, Wiegmann, Rich et al. 2010) and they also reflect real-world reliability results for such systems, e.g., (Wang, Cardone et al. 2012, Liu, Pu et al. 2015). In the 80% and 90% trials, alerts could come either early or late, and were counterbalanced. False alarms were not within the scope of this study. Participants in the 80% condition experienced either a late or early alert 6 out of 30 trials, and 3 out of 30 for the 90% condition.

The Early alert activated at 260ft, which gave the pedestrian a 7s gap (E in Figure 1), and the Late alert occurred at 110ft leading to a 3s gap (L in Figure 1), which would be an extremely unsafe situation with a high likelihood of collision. In order to control for the precision needed in signaling the alerts at the precise early/just-in-time/late distances, a wizard-of-oz technique (Kelley 1984) was used where an observer initiated a signal to the phone which activated the alert.

As a participant approached the road as picture in Figure 3, the red octagon alert in Figure 2b was triggered by the App Alert Activator, along with the audio and vibration alerts. The car was in view for the late and just-in-time alerts, but not in the case of the early alert. While participants were expected to stop when alerted, some kept going until they reached the cones with the tape across them. Once participants stopped, they were immediately asked if they would have kept going regardless of the alarm. They were also asked if they thought the alarm was on time, early, or late. Then each participant would go back to their unique starting position and repeat this 29 more times with breaks as needed. Once they were finished with all the trials, participants filled out a survey asking about their likely use of such a device in the real world, thanked, and then compensated. Each experiment took 60-90 minutes.

Each participant executed 30 trials, leading to 900 test sessions. The design was between-subjects across the three levels of reliability. Measured variables included participants' answers as to whether they would have continued despite the alert, their assessment of the reliability of the alarm, whether they stopped when the alert triggered, and how far they stopped from the road's edge (measured to the nearest half foot).

RESULTS

Unsafe and Risky Crossings

The first question examined was how many trials would have resulted in an unsafe or risky crossing. Trials were labeled as unsafe if participants had a late alert and reported that they would still cross, or if they kept walking even after the alert told them to stop. Risky crossings were assigned to people in the just-in-time alarm group who reported they would have still crossed as well as those who kept walking after the alert was triggered. While participants were split evenly across the three reliability groups (300 observations in each), there were only 45 early trials and 49 late trials. Table 1 details the results from these 900 trials.

Table 1: The number of safe vs. risky vs. unsafe crossings as a function of time of arrival

	Safe	Risky	Unsafe
Early	45	0	0
Just-in-time	645	161	0
Late	33	0	16

Figure 4 illustrates how many late crossings were unsafe (33%) and how many just-in-time crossings were risky (20%), as a function of gender and nationality (unsafe base = 49, risky base = 806). A Chi square test for risky crossings was significant ($\chi 2 = 14.3$, $p < .0001$) but not significant for unsafe crossings ($\alpha = 0.05$). Asian males had the riskiest crossings, followed by Asian females, with American females as the least risky. Using a two factor ANOVA with nationality and gender as the factors and the total number of risky crossings per participant, nationality was significant ($F(1,29)=5.72$, $p = .024$) but gender was not.

Understanding whether participants actually perceived the different timing of the alerts sheds light on the results in Figure 4. To this end, participants were asked immediately after every trial whether they thought the alert was early, late or on time. Those with early alerts had the most aligned perception with only 11% of trials perceived incorrectly (seen as either on time or late). For those with just-in-time group (the bulk of the trials), 17% were seen as early with 10% seen as late. This is important since the people who perceived the alert as early exhibited an underestimation bias. Lastly, those in the late group perceived the alerts to be early 2% and 49% correct of the time respectively, both of which could be a

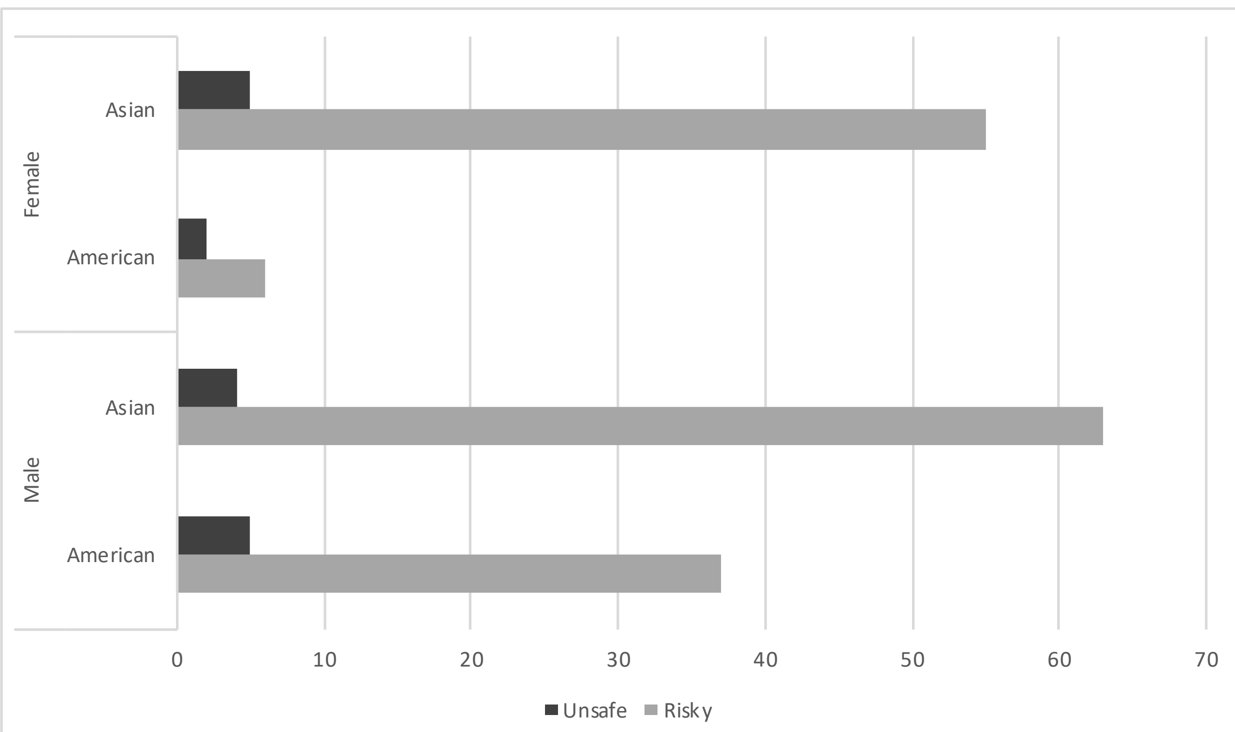

Figure 4: Risky and unsafe potential pedestrian crossings across gender and nationality

deadly underestimation bias and partly explains why there was such a big percentage of people in the late condition willing to cross. Taken together, 72% of participants were correct in their assessment of alert timeliness, but 18.4% demonstrated an underestimation bias that could have put them in danger.

Trust and Reliability

To further assess participants' perceptions of alert reliability, at the end of the experiment, participants were asked to estimate the overall reliability of the smartphone alerting systems. While there was no statistically significant difference between the three reliability groups considering nationality, the median estimate of people in the 80% reliability condition was that the system was 85% correct, while those in the 90% condition felt the system was, on average, 88% correct, and people in the perfect reliability condition felt the system to only be 90% correct.

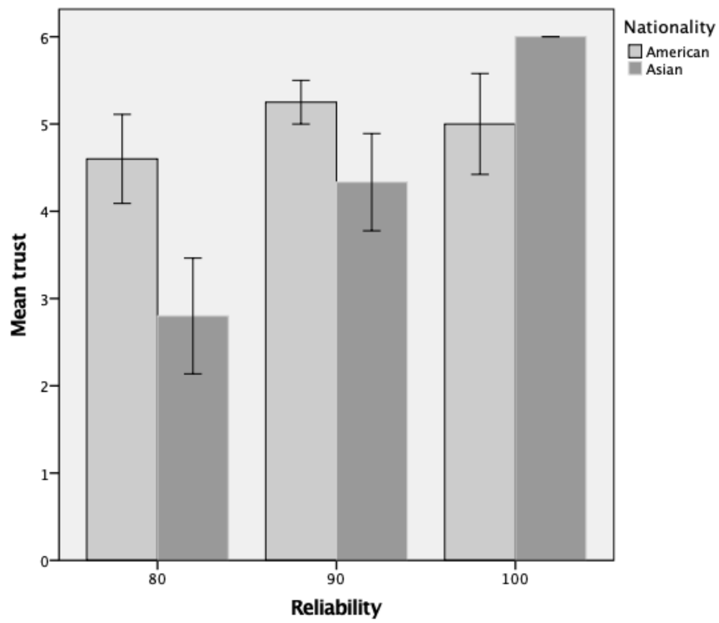

Figure 5: Average trust ratings (+/- 1 standard error) for 80, 90, & 100% alert reliabilities for Americans versus Asians.

When asked on a 7-point Likert scale how much they trusted the alert (1 = do not trust at all and 7 = completely trust), taking reliability, nationality and gender into account using an analysis of variance model, reliability is a statistically significant factor ($F(2,29) = 6.14$, $p = .009$). Moreover, as illustrated in Figure 5, there is a significant interaction between reliability and nationality ($F(2,29)=4.13$, $p = .033$), suggesting that Asians more accurately aligned their trust with the system's actual reliabilities.

Overall, 60% of participants felt they would use this alert app frequently. When people were asked whether they preferred the smartphone alert to their own judgment on a 7-point Likert scale, 43.4% of participants preferred the judgement of the app, 26.7% trusted their own judgment more and 29.1% thought they were equivalent. This relationship was particularly strong for older participants. Age significantly and strongly correlated with this judgment assessment ($\rho= .546$, $p = .002$), meaning older people were more likely to rely upon the app for correct alerts.

There was another strong correlation between the number of risky crossing per person and their neuroticism score (($\rho= .506$, $p = .006$), which means that those people with higher neuroticism scores made more risky crossings. People higher in neuroticism have a tendency to experience unpleasant emotions easily, such as anxiety and have been shown to be more distracted while driving (Johansson and Fyhri 2017) and to exhibit unsafe crossing behaviors (Zheng, Qu et al. 2017).

A Decision Tree Model

Given these inferential results, it is critical to understand how they relate in order to provide tangible and actionable recommendations to designers of both connected cars (with and without drivers), as well as designers of pedestrian crossings. To this end, a Classification and Regression Trees (CART) decision tree model was constructed since such trees are not sensitive to outliers, important in this relatively small data set (Loh 2011). Moreover, such an approach has been effective in modeling other pedestrian crossing data (Cummings and Stimpson 2019).

To this end, the unsafe and risky crossings from the earlier analysis were combined to form the target variable of safe vs. risky, and the features included nationality and neuroticism scores, as the inferential analysis showed them to be important variables. Thus, there were 726 safe and 177 risky crossings. A third feature, stopping distance, was added since people sometimes stopped before an alert or kept walking after the alert, and this distance could signal a person's willingness to take risk. Using crossvalidation (10 folds), this model yielded an overall accuracy of 83.3%.

Figure 6 illustrates the resulting decision tree with 9 nodes. Each of the terminal nodes with a number represents the safe/risky crossing ratio for the combination of features (higher number means higher likelihood of safe crossing). For example, those with Neuroticism scores under 21.5 and stopping distances of more that 2.25 ft were 48 times more likely to have a safe crossing. Conversely, Asians with a neuroticism score of over 21.5 and a stopping distance of less than 1.75 ft were twice as likely to put themselves in an unsafe situation. A neuroticism score of 21.5 occurs at the midpoint of typical neuroticism scores as measured by the Baltimore Longitudinal Study of Aging sample (McCrae and Costa 2004).

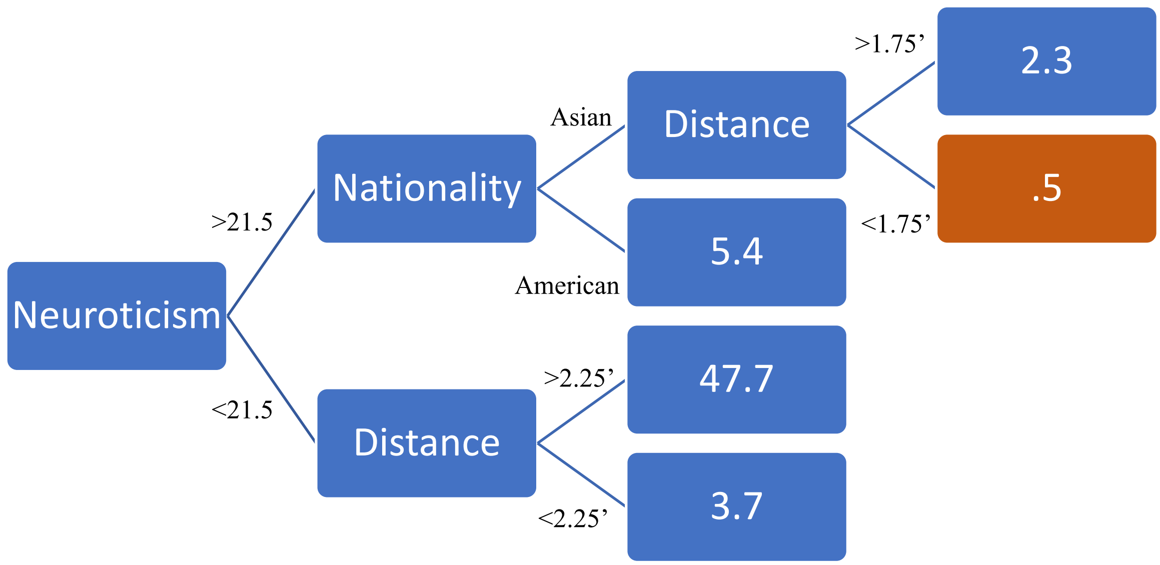

Figure 6: Decision tree analysis demonstrating neuroticism scores were a strong predictor of safe vs. risky crossings, with nationality and stopping distances as relatively equally-weighted factors. The terminal nodes with a number represent the safe/risky crossing likelihood of that particular group.

DISCUSSION

This study originally intended to look at the behaviors of pedestrians crossing a road while texting on a smartphone that would also alert them to the presence of an oncoming car, with varying degrees of reliability. While not originally planned, an opportunistic experimental factor emerged in the form of comparing Americans with an equal number of participants from Asia. Indeed, this cultural difference is one of the strongest results of this study.

In looking at the number of potentially unsafe crossings (Figure 1), 20% of crossings were risky or unsafe, with the bulk of these happening when an alert was given at a time that allowed participants to have *just* enough time to safely cross. When the alert was late, the percentage of unsafe crossings were just 2% of the total number of crossings, but 33% of the late crossing attempts. More than 18% of participants exhibited underestimation bias and thought the car was farther away than it really was. These numbers of risky crossings align with other observational research studies looking at typical pedestrians, 21% of observed crossings at an intersection in Brisbane Australia were risky (King, Soole et al. 2009), 20% of crossings in Seattle were against the light (Thompson, Rivara et al. 2013), and 21% of pedestrians in Vancouver, Canada committed pedestrian road-crossing violations at high-incident pedestrian injury intersections (Cinnamon, Schuurman et al. 2011).

Asians statistically had the highest number of risky crossings in the presence of oncoming cars when compared to Americans. The highest number of risky crossings for an individual male was 21 out of 30 while the highest for an individual female was 20 out of 30 and both were Asian. While other pedestrian studies have reported that males engage in more risky behaviors that females (Zhu, Zhao et al. 2013, Deba, Strawderman et al. 2017), this study did not find any statistical differences in actual behaviors, likely due to low numbers and a bimodal distribution in Asian women, in that they either had 0 risky crossings or 8-20. One of the more curious findings is that even though Asians as a group were more likely to attempt risky crossings while engaged in distracted walking, they also trusted the alert less when it generated early and late warnings. So even though Asians appropriately increasingly distrusted the alerting system as it performed less reliably, this did not deter them from making more risky crossings.

The CART decision tree (Figure 6) sheds further light on the nature of risky crossings and demonstrates that the most potentially risky crossings occurred for Asians who scored above 21.5 on the NEO-FFI neuroticism scale, especially those who were willing to walk within 1.75 feet of the roadway's edge. The best odds for safe crossings were those people who scored lower on the neuroticism scale and were more conservative in their stopping distance of greater than 2.25 ft. The CART analysis also illustrates the strength of the neuroticism variable, which contributed the most to the model. In a previous study, neuroticism was also associated with more unsafe pedestrian crossings and a lack of attention for Chinese people (Zheng, Qu et al. 2017), with raw scores very similar between the two studies.

These results indicate a strong cultural influence in pedestrian attitudes towards crossing, which has been seen in other studies. In a field observation study in China, 66% of pedestrians crossing an unmarked roadway did not look for oncoming vehicles (Zhuang and Wu 2011). Other studies have noted Chinese pedestrians who use mobile phones while crossing unsignalized intersections are at higher risk than those with no phones (World Health Organization 2015, Zhang, Zhang et al. 2017).

China is not the only country, of course, to have such problems. In one observational study in France, 42% of crossings occurred against the light compared to just 2% in Japan. Researchers hypothesized that this difference was due to the Japanese concern about the opinions of others whereas the French have less need for social approval (Pelé, Bellut et al. 2017). Even within the US, there are very different cultural behaviors in pockets of society that lead to higher pedestrian injuries and fatalities leading one researcher to comment, "developing effective pedestrian crash reduction strategies in ethnic neighborhoods may deserve further study (Zegeer, Henderson et al. 2008)."

While not part of the formal experiment, more than two dozen Chinese and Indian faculty and students were asked to comment on these results. All agreed that the results reflected their personal experiences, both in the US and in their respective countries. The most common explanation put forth is that Asians tend to look at road crossings as negotiations in their countries as opposed to rule-driven events in America. Several commented that they viewed a crossing more as wading into traffic as opposed to crossing in a guaranteed space.

More research is needed to examine these theories in more detail but understanding these divergent viewpoints is needed in order to inform both vehicle and infrastructure design in the future. As cars with more automation increasingly move into various cultures, it is not clear that software designed in Silicon Valley that models rule-abiding pedestrians in the US will perform in the same way if deployed to a country in Asia, France, or any other number of countries. In addition, the creation of safer, more protected pedestrian spaces in countries where people routinely ignore crossing signals and warnings is another area of needed research.

Lastly, these results call into question the use of alerts on a smartphone meant to stop people from walking into traffic. This study falls in line with a number of other simulator studies that show alerts on mobile phones are not particularly useful and may encourage maladaptive behaviors and an overreliance on alerts (Rahimian, O'Neal et al. 2018, Rahimian, O'Neal et al. 2018). It should be noted that overall in this study, people trusted the alert app more than they did their own judgment, even when the app generated late alerts. This study demonstrates just how critical the timing is for these devices and if such alerts are even a second late, the results could be fatal.

Putting visual alerts on the vehicles has not produced particularly encouraging results (Clamann, Aubert et al. 2017), so the electronic warning approach may not be not the best. To this end, another group of researchers tried the analog approach of simply painting "Heads Up, Phones Down" near intersections. This intervention produced statistically significant less texting, but compliance eroded over time, suggesting a type of risk homeostasis, (Barin, McLaughlin et al. 2018). Clearly, more research is needed to find solutions, both in terms of technology and infrastructure design, to help mitigate what will be a growing problem.

<u>Limitations</u>

There are a number of limitations that should be considered in evaluating these results. The CART model accuracy was 83.3% suggesting that other unmeasured variables could have improved the predictive accuracy. In addition, this experiment generated a small number of unsafe and risky trials (177) versus 723 safe trials from 30 participants. This results in a somewhat unbalanced data set. Such field-based controlled experiments are extremely difficult to conduct which inherently limits the numbers of participants. Access to large data sets of actual crossing behavior could significantly advance knowledge in this area, which has also been recently noted by the National Transportation and Safety Board (NTSB 2018).

Another limitation is that in each of these experiments, only a single person attempted a crossing. Especially in urban environments, clusters of people often cross and the presence of other people can dramatically influence the behaviors or others. Previous research has demonstrated that when pedestrians are in a group, they tend to exhibit more aggressive behavior (Wang, Wu et al. 2010), perhaps akin to a herd mentality, so it remains to be seen how these results would change as number of pedestrian increased. In addition, participants were cooperative in this study, but recent research suggests that if and when driverless cars become more commonplace, pedestrians could game these vehicles given that they know they will be programmed to be safe and potentially conservative in urban settings (Millard-Ball 2018). Thus, non-cooperative behaviors also need further study.

CONCLUSION

Globally, pedestrian deaths account for almost a quarter of all traffic related deaths and are also increasing (World Health Organization 2018). In the US, pedestrian fatalities now account for approximately 16% of all motor vehicle crash-related deaths (Retting 2018), with an 81% increase in injuries to distracted pedestrians since 2005 (Nasar and Troye 2013). These increasing injury and fatality rates are concerning given that cars, in theory, have more safety devices on them today than ever before. Moreover, with increasing worldwide focus on autonomous self-driving vehicles, it is not clear that such advanced technology can account for vulnerable users such as pedestrians. It is not clear how much pedestrian risk will be increased with the arrival of more automated vehicles and what could be done to mitigate such risks when these cars are more commonplace.

This research effort demonstrated that in a group of 30 participants who were given smartphone aural and visual alerts of varying reliability while engaging in distracted walking, only 2% exhibited a tendency towards unsafe crossings, while 18% tended towards risky crossings. These results parallel similar observational studies. Asians, representing half the test population, were statistically more likely to engage in risky crossing behavior despite developing accurate trust models of the alert reliability. This was particularly true for Asians with higher than average neuroticism personality scores.

These results suggest that culture plays an important role in the use of technological interventions meant to promote positive behaviors and that a solution effective in one setting may not generalize to other cultures. Moreover, technology-focused interventions are currently not producing solutions that are effective, especially across different cultures. While the subject pool was small in this study and more research is needed in larger population, this research suggests that that there may design criteria that can be elucidated from such use of machine learning classification methods in concert with controlled experiments. In this experiment, whether people stopped at or before approximately two feet from the road's edge predicted that would likely have a safer crossing. Such a threshold could be critical for the designers of autonomous cars that need to prioritize the tracking of multiple entities in congested environments. Those pedestrians that move, for example, inside two feet with constant or increasing velocity or acceleration can become high priority entities to track.

More research is needed to determine such thresholds, including variations due to culture, road and sidewalk design, and proximity to particularly vulnerable populations, i.e., high school and college campuses with higher number of people like to engage in distracted walking. However, given that cars like Teslas and Waymo's self-driving vans already collect this information at levels researchers never could, allowing non-partisan researchers to access this data and develop safety-based models to be shared across all manufacturers would help prevent future fatalities.

Acknowledgments

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