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Development and Evaluation of Vehicle to Pedestrian (V2P) Safety Interventions

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16. Abstract

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 recent research 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 system, 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. More than 18% of participants exhibited underestimation bias and thought the car was farther away than it really was. While international participants (i.e., on-US-born) 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.

These results suggest that national origin may play 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 nations. 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, this research suggests that there may design criteria that can be elucidated from such use of machine learning classification methods in concert with controlled experiments.

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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 (Schaper, 2017; Swanson, Yanagisawa, Najm, Foderaro, & Azeredo, 2016). One study has shown that injuries from distracted walking have increased 81% since 2005, with those 16-25 years old affected the most (Nasar & Troye, 2013). In one observational study in Seattle, approximately 30% of all pedestrians observed performed a distracting activity while crossing (Thompson, Rivara, Ayyagari, & Ebel, 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 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, & Nurminen, 2014; Bai & 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, Corradi, Torresani, & Campbell, 2012).

While such devices could, in theory, help to mitigate pedestrian accidents and fatalities, it is not clear if such benefits can be achieved in practice. Research has shown people often tend to ignore emergency alerts from their mobile phones (Kar & Cochran, 2016). Moreover, alert fatigue, which occurs when people are desensitized to frequent alerts, routinely occurs in safety-critical settings such as healthcare (Ancker 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 & 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 et al., 2018).

Given that alerting systems are not perfect, especially when detecting moving vehicles at short distances, it is not clear if smartphone alerts 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.

Method

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 of the two, primarily due to the difficulties in controlling both vehicle and foot traffic (e.g., Papadimitriou, Lassarre, & Yannis, 2016). Self-reports of pedestrian behavior have been shown to be biased towards positive behaviors such as traffic rule compliance (Deba et al., 2017) so it is often difficult to capture realistic behaviors.

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 list serves and flyers in the local Garysburg, NC area as well as the Raleigh-Durham metro area. While not part of the original design, half of the participants self-identified as US born and half grew up in other countries (9 China, 5 India, 1 Saudi Arabia). Because of this opportunistic development, the half not from the US were labeled as non-US-born. This resulted in 10 and 5 US-born males and females, respectively and 8 and 7 non-US-born males and females, respectively. 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. All participants met the screening requirements.

Test Environment

Some pedestrian studies have used immersive simulators (e.g., Feldstein, Dietrich, Milinkovic, & Bengler, 2016; Rahimian, O'Neal, Zhou, Plumert, & Kearney, 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 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.

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.

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 while crossing. 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 experienced. 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 the phone 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, agreeableness, and conscientiousness. Previous similar research has shown that people with higher conscientiousness scores cross faster than those with lower scores (Clamann, Aubert, & Cummings, 2017).

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

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 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 an experimenter 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).

Thus, for each trial, a participant started somewhere in the vicinity of point S (Figure 1) and then walked towards the road as depicted in Figure 3 while playing the maze. In most trials, the alert triggered at Point I in Figure 1 when the car was 185 ft away, which gave the participant a 5s gap to cross the road. 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 et al., 2013).

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.

Each car 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 so that the alarm on the phone could be manually triggered to ensure correct timing for the early, just-in-time, and late alerts. The person who triggered this alarm was called the App Alert Activator, located at position 3 in Figure 1.

Experiment Design

Participants were randomly 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, Hancock, Barnett, & Taylor, 2008; Wiegmann, Rich, & Zhang, 2010) and they also reflect real-world reliability results for such systems, e.g., (Liu et al., 2015; Wang et al., 2012). 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 when the car was 260 ft from a participant, which gave the pedestrian a 7s gap (E in Figure 1), and the Late alert occurred at 110 ft 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 exact early/just-in-time/late distances, a wizard-of-oz technique (Kelley, 1984) was used where an observer, the App Alert Activator, initiated a signal to the phone which triggered the stop sign alert on the phone.

When a participant approached the road as pictured in Figure 3, the App Alert Activator triggered the red octagon alert, along with the audio and vibration alerts (Figure 2b). 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 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 returned to their unique starting position and repeated this procedure 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.

During the two practice sessions, participants were not instructed nor given any feedback as to their assessments of the timeliness of the alert. Each participant’s 30 trials led 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. Unsafe trials occurred if participants experienced a late alert and reported that they would still cross, or if they kept walking even after the alert told them to stop. This was labeled unsafe since the gap was only 3s and as mentioned previously, a typical adult could cross a single lane in 2.7s, assuming no slips, trips or falls. With only a 5s gap, risky crossings occurred for 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. People in the early group could not make an unsafe or risky crossing, assuming they did not delay significantly in their decision. 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 (percentage of total) of safe vs. risky vs. unsafe crossings as a function of time of alerting

	Safe	Risky	Unsafe	Total
Early	45 (5%)	0 (0)	0 (0)	45 (5%)
Just-in-time	645 (71.6%)	161 (18%)	0 (0)	806 (89.6%)
Late	33 (3.4%)	0 (0)	16 (2%)	49 (5.4%)
Total	723 (80%)	161 (18%)	16 (2%)	900

The overall percentage of late crossings that were unsafe was 33%, with 20% overall of risky just-in-time crossings. Figure 4 illustrates the percentages as a function of gender and nationality (unsafe base = 49, risky base = 806). The highest number of risky crossings for any male was 21 out of 30 while the highest for any female was 20 out of 30 and both were non-US-born participants. Non-US-born females had the highest percentage of riskiest crossings, followed by non-US-born males, with US-born females as the least risky. Using a Chi-Square test for proportions, nationality (US-born vs. non-US-born) was significant for risky crossings ($\chi 2 = 44.7$ $p < .0001$) but not for unsafe crossings ($\alpha = 0.05$). Gender was not statistically significant for either variable.

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 in that they perceived the car to be farther away than its actual distance, which underestimates the risk. Lastly, those in the late group perceived the alerts to be early 2% of the time, while 49% were seen as on time, both of which could be a 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 overall were correct in their assessment of alert timeliness, but 18.4% demonstrated an underestimation bias that could have put them in danger.

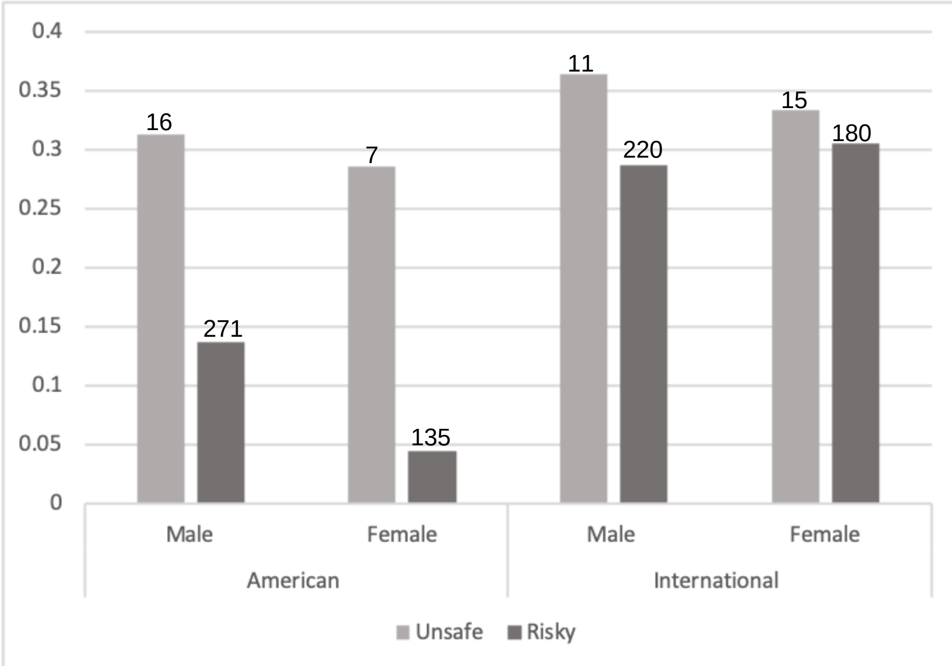

Figure 4: Percentages of potential risky and unsafe pedestrian crossings across gender and nationality. The total number of observations is reported above each bar.

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 system (Table 2). 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.

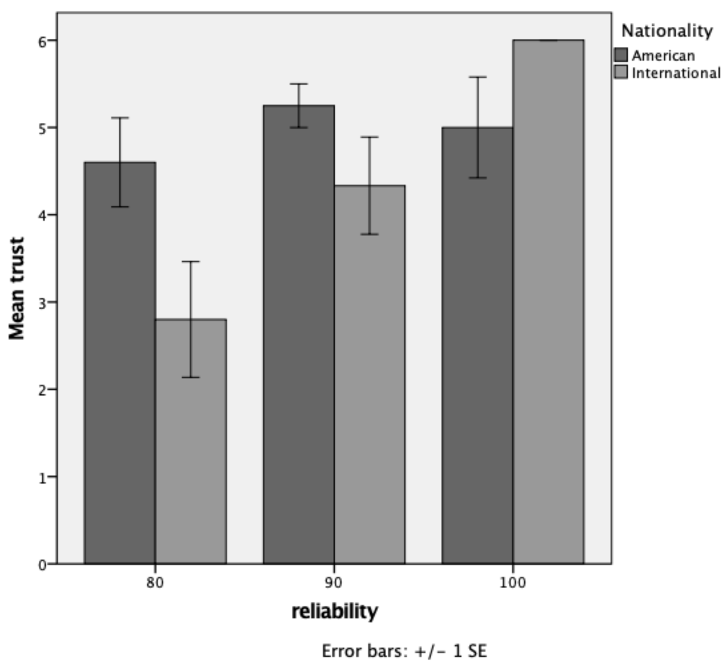

Figure 5: Average trust ratings (+/- 1 standard error) for 80, 90 & 100% alert reliabilities for US-Born vs. Non-US Born.

When asked on a 7-point Likert scale how much they trusted the alert (1 = do not trust at all and 7 = completely trust, Table 2), taking reliability, nationality and gender into account using an analysis of variance model with all assumptions met, 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 non-US-born participants 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 judgment 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 on the app for correct alerts.

Table 2: Descriptive statistics for estimated reliability and trust

	Mean	Median	Standard dev.	Min	Max
Estimated reliability (%)	79	89	22	20	100
Trust (1 = no trust, 7 = complete trust)	4.6	5	1.45	1	7

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 & Fyhri, 2017) and to exhibit unsafe crossing behaviors (Zheng, Qu, Ge, Sun, & Zhang, 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 in SPSS 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 & Stimpson, 2019).

CART is a non-parametric supervised machine learning algorithm wherein a tree structure decomposes a dataset into subsets, resulting in a decision tree with branch nodes and leaf nodes. Each branch node corresponds to a feature variable and each leaf (or terminal) node corresponds to a class label, in our case, safe vs. risky. CART creates data subsets by analyzing different categorical groupings and minimizing the variance in the groups. It recursively searches and splits categories until a stop criterion is reached (Hastie, Tibshirani, & Friedman, 2017).

Using CART, 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 cross validation (10 folds), the Gini splitting criterion, and a maximum tree depth limit value of 5, this model yielded an overall accuracy of 83.3%.

Figure 6 illustrates the resulting decision tree and 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, non-US-born participants 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 & Costa, 2004).

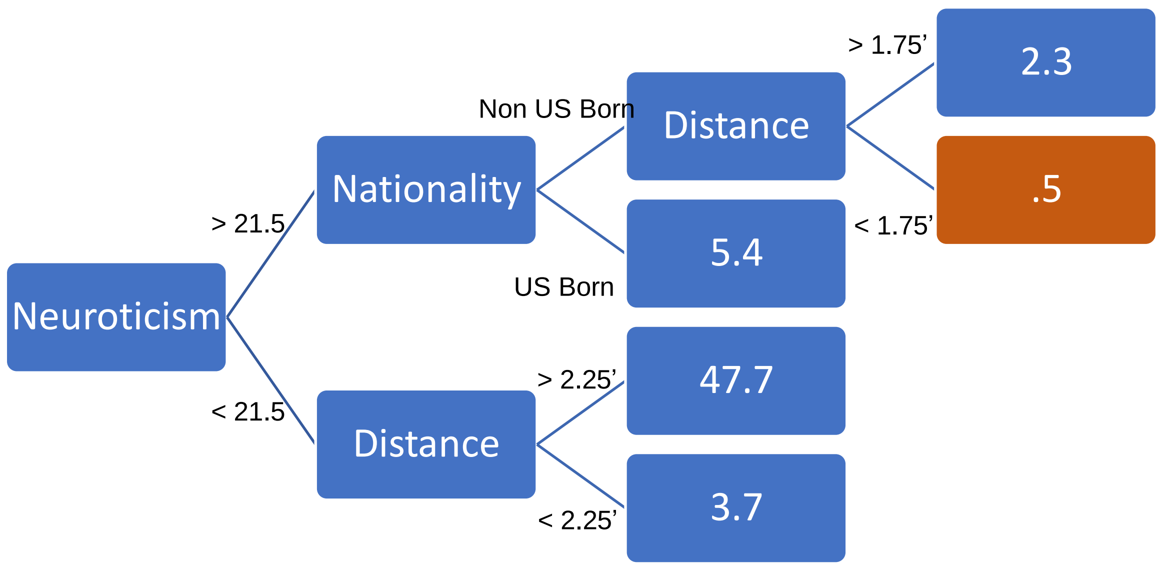

Figure 6: Decision tree analysis demonstrating neuroticism scores were a strong predictor of safe vs. risky crossings, with nationality and stopping distances as relatively equally-weighted factors. The terminal nodes with a number represent the safe/risky crossing likelihood of that particular group.

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 US-born participants with an equal number of participants from other countries. Indeed, this 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 percentages of risky crossings align with other observational research studies looking at pedestrian behaviors, including 21% of observed crossings at an intersection in Brisbane Australia that were risky (King, Soole, & Ghafourian, 2009), 20% of crossings in Seattle against the light (Thompson et al., 2013), and 21% pedestrian road-crossing violations at high-incident pedestrian injury intersections in Vancouver, Canada (Cinnamon, Schuurman, & Hameed, 2011).

Non-US-born participants statistically had the highest number of risky crossings in the presence of oncoming cars when compared to US-born participants. While other pedestrian studies have reported that males engage in more risky behaviors than females (Deba et al., 2017; Zhu, Zhao, Coben, & Smith, 2013), this study did not find any statistical differences in actual behaviors due to gender. One of the more curious findings is that even though non-US-born participants 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 the non-US-born participants 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 non-US-born participants 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 et al., 2017), with raw scores very similar between the two studies.

These results indicate that there may be differences in crossing behaviours by pedestrians born outside the US, and that further research is needed to identify potential differential effects of interventions, 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 & 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, Wei, & Chen, 2017). In another 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 et al., 2017). Even within the US, there are very different behaviors in pockets of society related to higher pedestrian injuries and fatalities (Zegeer et al., 2008).

More research is needed to examine how national origin influences crossing behaviors in more detail but understanding different crossing behaviors is needed in order to inform both vehicle and infrastructure design in the future. As cars with more automation increasingly move into various nations, it is not clear that software designed in Silicon Valley that models pedestrians in the US will perform in the same way if deployed to a country in Asia, France, or any other number of countries.

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 et al., 2018; Rahimian 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 such alerts and if even a second late, the results could be fatal. In addition, while there appeared to be a national origin influence towards crossing attitudes with such a device, more work is needed to determine whether such alerting devices may be more effective in a variety of settings.

Putting visual alerts on the vehicles has not produced particularly encouraging results (Clamann 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 significantly less texting, but compliance eroded over time, suggesting a type of risk homeostasis, (Barin, McLaughlin, McLaughlin, Farag, & Arbogast, 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.

Limitations

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. Additional experiments could be run using the tools and procedures outlined in the Method section, but this experiment protocol required a closed course, which can be a significant constraint. Access to large data sets of actual crossing behavior could also 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 together 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, Zheng, & McDonald, 2010), perhaps akin to a herd mentality, so it remains to be seen how these results would change with an increase in the number of pedestrians. 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 & 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 also 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, the first to conduct a controlled experiment of crossing pedestrians in a field setting with smartphone-based alerts, demonstrated that in a group of 30 participants 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. Non-US-born participants, 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 non-US-born participants with higher than average neuroticism personality scores.

These results suggest national origin plays an important role in the use of technological interventions meant to promote positive behaviors and solutions effective in one setting may not generalize to other nations. Moreover, technology-focused interventions are currently not producing effective solutions, especially across different nationalities. While the subject pool was small in this study and more research is needed in a larger population, this research suggests design criteria might 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 safer crossings. Such a threshold could be critical for the designers of autonomous cars who 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 nationality, road and sidewalk design, and proximity to particularly vulnerable populations, i.e., high school and college campuses with higher numbers of people like to engage in distracted walking. However, given that cars like those from Tesla and Waymo 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.

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