Communicating Intent in Autonomous Vehicles

by

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ABSTRACT

The prospects of commercially available autonomous vehicles are surely tantalizing, however the implementation of these vehicles and their strain on the social dynamics between motorists and pedestrians remains unknown. Questions concerning how autonomous vehicles will communicate safety and intent to pedestrians remain largely unanswered. This study examines the efficacy of various proposed technologies for bridging the communication gap between self-driving cars and pedestrians. Displays utilizing words like "safe" and "danger" seem to be effective in communicating with pedestrians and other road users. Future research should attempt to study different external notification interfaces in real-life settings to more accurately gauge pedestrian responses.

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INTRODUCTION

The age of autonomous vehicles (AV's) is quickly approaching and ushering with it new roles for human agents. These new roles will be enabled by the emergence of technologies that account for all aspects of the driving experience and promise to replace the rote, oftentimes mundane, features of driving that currently require humans to tend to road conditions, adhere to variable speed limits, and watch for cyclists and pedestrians. This will help free up the estimated three-hundred hours, or approximately two-weeks, Americans spend driving annually for better use elsewhere (Bureau of Labor Statistics, 2018, 60). Current forecasts from industry professionals suggest level four AV's will comprise 90-95% of new car sales by 2030 with an estimated market cap of \$3.6 trillion-dollars (Munster, 2017). Level four automation means that vehicles will be able to pilot themselves in nearly all driving scenarios, while relying on human intervention when faced with unexpected conditions. This effort is being spearheaded by car manufacturers and tech giants alike, who, lured by promises of massive financial windfall, have committed to bringing AV's to market (Munster, 2017). Although the bulk of research in the field has been devoted to the automation which will enable these vehicles, little has been committed to examining the ramifications of this potentially disruptive technology in relation to other road users.

AV's promise to improve transportation by leveraging the power of machine learning algorithms in conjunction with increasingly sophisticated cameras and lidar technologies. These vehicles, though revolutionary, come ridden with novel safety concerns that pose unique challenges for all parties involved (Mahadevan et al, 2017). Among the most pressing of these is the issue of communication between operators of AV's and pedestrians in the immediate area. As it stands, drivers and pedestrians rely on a combination of verbal and nonverbal strategies to

communicate intent to one another. These strategies range from distinct gestures to subtle eyecontact and work to ensure the safety of drivers and pedestrians alike. The rise of autonomous
vehicles threatens to upend this relationship as agency is diverted from drivers to machines and
pedestrians are left wanting. Meaningful solutions to this novel challenge have proven elusive.

Concerted efforts across industries have been made to bridge the communication gap between
AV's and humans (Mahadevan et al, 2017). Proposed solutions include shifting color gradients
in vehicle headlights (green to go, red to stop), outfitting cars with large digital displays that spell
out intentions, vehicles capable of projecting signals to pedestrians, and much more (Rasouli &
Tsotos, 2018). Proposals have, thus far, had limited real-world impact as the bulk of
comprehensive testing remains either in its infancy or behind the closed doors of automotive
manufacturers jockeying for technological supremacy. This poses existential risks for pedestrians
as the social dynamics of driving unravel and are replaced by recondite predictive algorithms.

LITERATURE REVIEW

Driver and Pedestrian Interactions

The effective use of public streets and roads relies upon the adoption of, and adherence to, rules governing speed limits, stop signs, etc. Once codified, these rules from the basis of traffic and traffic infrastructure. In addition to laws which govern the rules of the road, drivers and pedestrians also apply an additional layer of social complexity to facilitate ambulation and transit. This complexity generally manifests itself in the form of dynamic social cues and includes eye contact, waving, nodding, etc. (Rasouli, Kotseruba, & Tsotsos, 2017). These nonverbal strategies are essential in safely navigating ambiguous situations and form the crux of driver-pedestrian interactions.

Pedestrians intending to cross busy streets instinctively look about and attempt to make eye contact with drivers; and for good reason (Rasouli et al., 2017). Eye contact plays a pivotal role in establishing communication and is oftentimes the primary mode in negotiating how streets and roads are to be shared between road users (Gueguen, Meineri, & Eyssartier, 2015). For example, a pedestrian seeking to cross the road in the absence of stop signs may opt to establish eye contact with motorists before deciding to cross. For this to work, the parties in question must be receptive to one another. If eye contact is established, drivers and pedestrians can begin conveying information about when to cross or whether to wait for vehicles to pass. Conversely, if eye contact is not established, pedestrians can assume their intentions have gone unnoticed and must wait until their efforts are reciprocated. This view is supported by results from researchers Schmidt and Farber (2009) who found that both drivers and pedestrians prioritize eye contact over other communication strategies in road settings. Their study showed that, absent of other contextual information, participants could not accurately determine the intentions of pedestrians based solely on their physical trajectories (Schmidt & Farber, 2009). Instead, eye contact and other nonverbal indicators were necessary before participants could accurately discern pedestrian goals.

The primacy of eye contact as a means of negotiating safe passage on busy streets and roads has been explored in a variety of settings. In their study detailing behaviors of road users at busy intersections, researchers Suchaa, Dostal, and Risserin (2017) found that 84% of pedestrians looked to establish eye contact with drivers before committing themselves to crossing streets; however approximately 36% of drivers ignored situations in which they were required to yield to pedestrians. This led to dangerous situations in which pedestrians, aware of their right-of-way priority, would attempt to cross streets only to be met with unyielding drivers

(Suchaa, et al., 2017). Researchers diagnosed poor driver yielding as symptomatic of inadequate visual communication between motorists and pedestrians. Gueguen, et al. (2015) studied the role visual communication played in pedestrian and motorist interaction by splitting participants into two groups. One group would make eye contact with motorists, and the other would rely on body language for communication. The researchers discovered that motorists would yield to pedestrians 68% of the time if eye contact had been established in right-of-way settings. However, if pedestrians were acknowledged, but eye contact was not established, drivers yielded far less often, despite finding themselves in identical situations (Gueguen, et al., 2015). Numerous studies have corroborated these results and point to the intrinsic utility of eye contact in facilitating the safety and flow of traffic.

The implications of behavioral research between motorists and pedestrians offers insights which may facilitate the large-scale integration of AVs in public streets and roads. Design solutions for building effective channels of communication between AVs and pedestrians have relied on peoples' predilections for seeking eye contact (Habibovic, et al. 2017). This is in large part due to studies which have revealed pedestrian insecurities when interacting with traditional motor vehicles (Lundgren, Habibovic, Andersson, Lagstrom, Nilsson, & Sirkka, 2017). For example, pedestrians consistently cite driver distraction and inattention as primary causes for concern when navigating intersections (Lundgren et al., 2017). This trepidation extends to interactions with AVs too, as pedestrians display similar levels of discomfort when dealing with AVs as they do with distracted drivers (Lundgren et al., 2017). This suggests the origins of pedestrian anxiety are not rooted in any meaningful bias against AVs, but rather stem from inadequate communication techniques. The literature supports this assertion, as findings suggest

designing vehicles which clearly spell out intentions may be instrumental in building trust and confidence in autonomous systems (Habibovic et al., 2017).

Adopting Automation

Autonomous technologies have radically changed traditional human roles in a variety of sectors including manufacturing, engineering, medicine, and more. This has had transformative effects in shaping the human condition as the merger of man and machine has resulted in increased productivity, more affordable services, and greater quality of life (Chui, Manyika, Miremadi, 2015). As automation becomes more sophisticated and encroaches even further into fields long thought to be immune to its effects, the issue of trust arises; specifically, as it relates to the adoption and implementation of technology.

Trust is imperative when building cooperative networks whether with humans or machines. Researchers Lee and Moray (1992) identified purpose, process, and performance as defining factors which determined user's willingness to adopt automated technologies. Their study had participants manage a simulated processing plant requiring them to decide which features to automate, and which they would control themselves for optimal performance.

Financial compensation was dependent on successfully managing the component parts of the simulation. Results from the first trials showed an unwillingness from participants to trust autonomous variables as they opted to manually exert control over most aspects in the simulation (Lee & Moray, 1992). Later trials showed the opposite; as participants became more acquainted with the technology, they relied upon it more and more (Lee & Moray, 1992). This led the researchers to conclude that successful adoption required users to understand the role of automated technologies, the processes in which they operate, and the reliability of their performance (Lee & Moray, 1992). Other studies have proposed similar trimodal components of

trust building. Researchers Thatcher, McKnight, Baker, Arsal, and Roberts (2011) identified functionality, helpfulness, and predictability as factors which deeply influenced the use and exploration of new technologies. Their study required participants to explore a series of digital platforms and answer questionnaires regarding use. Cross examining the time participants spent navigating platforms in conjunction with data collected from questionnaires showed researchers that functionality, helpfulness, and predictability were primary motivators for adopting new technologies (Thatcher et al., 2011). These results are in line with many findings which confirm similar relationships.

Building suitable levels of trust in automated machinery has long been a goal for industry experts and is complicated by several variables. Build too much trust into a system, and users become over-reliant on the technology; build too little, and users are unlikely to find it useful or desirable. One of the most important models in addressing these issues is the technology acceptance model (TAM). TAM emphasizes the role of usefulness and ease of use in forecasting the implementation of novel devices (Ghazizadeh, Peng, Lee, & Boyle, 2012). Studies suggest automated technologies that incorporate human elements into their design are more easily adopted by their human counterparts (May, Dondrup, & Hanheide, 2015). This is because engineering familiarity into machines can help mitigate the loss of peer-to-peer interaction between humans (Duffy, 2003). May, et al. (2015) found that a robot's ability to relay both attention and intention to humans was an important predictor of perceived usefulness. Participants rated comfort, safety, and desirability higher in trials in which mobile robots established gaze and communicated intent to them (May et al., 2015). Similar research suggests that robots that are more predictable are considered competent and easy to use (Takayama, Dooley & Ju, 2011). This may be essential in promoting good-faith collaboration between people and machines as autonomous technologies become more pervasive in everyday life (Goodrich & Schultz, 2007).

The TAM provides a general framework for designs that may be best suited for bridging the communication gap between AVs and other road users. Possible designs include anthropomorphic faces or smiles that mirror the implicit functionality of a human driver's social cues (Mahadevan et al., 2017). Such a design would promote familiarity and utility in AVs by incorporating a recognizable stimulus on an otherwise novel technology (May et al., 2015). Other solutions have opted to use LED strips attached to the front of cars to gauge the efficacy of written instructions in communicating intent to pedestrians (Habibovic, et al., 2017). Results from Habibovic, et al. (2017) suggest the use of key phrases like "stop", "go", "I'm waiting", etc. can be useful substitutes for human agents. Other proposals have argued that incorporating existing traffic signals onto digital displays may be most effective in engaging pedestrians (Mahadevan et al., 2017). Traffic signals like the stop sign are universally recognized for their unique shape and are ubiquitous on streets and roads. Aspiring AV manufacturers like Mercedes, Ford, and Google have demonstrated concept vehicles which communicate to pedestrians by displaying and projecting common traffic signals but have not made available the data that led them to their conclusions (Mahadevan et al., 2017; Mercedes-Benz, 2015; Google, 2016).

Current Study and Hypothesis

The goal of the following research is to offer greater insights into AV-pedestrian interactions by studying proposed solutions for communicating intent. Current research in the field is inconclusive as to which stimuli may be most potent in alerting pedestrians. A survey was designed to test the saliency of written messages, traffic signals, and anthropomorphic faces and smiles. It was predicted that displays with written images like "stop" and "go" would be

most effective in communicating intent to pedestrians. This hypothesis is supported by findings from Habibovic et al. (2017) and Lundgren et al. (2017) which have demonstrated pedestrian receptivity to the use of key phrases by AVs.

METHODS

Participants

Participants for the study consisted of 124 volunteers from the Mechanical Turk, mturk, community. Participant identities and sensitive information were protected via the anonymity provided on the mturk platform. There were two restrictions placed on participation: language and age. The survey used in the study was written exclusively in English and no translations were made. Therefore, only participants fluent in English were able to complete it. Age was also a discriminating variable, as all participants had to be 18 years or older before volunteering. Volunteers were compensated \$0.25 cents upon completing the survey. This amount is in-line with standard mturk compensation rates for projects of similar length and scale. Survey materials and study procedures were in accordance with the standards of the Institutional Review Board, IRB, at Arizona State University.

Materials

The survey was created on the Qualtrics platform and all images used were compiled from a combination of stock sources and photo-editing software. Adobe Photoshop and Microsoft 3D Paint were used to create all survey images. Images were intended to represent suggested solutions for bridging the communication gap between autonomous vehicles and other road users. Completion of the survey required basic internet connectivity and computer accessibility. The survey and corresponding materials are listed in the appendix section.

Design

The experiment utilized a 3x2x3 within-subjects design to assess which technologies were most effective in communicating intent to pedestrians. The variable for stimuli had three levels: written, traffic, and anthropomorphic visual displays. Each of the aforementioned levels of the stimuli included displays instructing participants that it was safe to cross, dangerous to cross, or neutral (responses to neutral were not included in the analysis). There were three instances of each of the 9 types of signals resulting in 27 stimuli. We identified signal comprehension as the dependent variable in our experiment and measured crossing behaviors in relation to the different display technologies. Displays were meant to assess proposed notification systems for communicating autonomous vehicular intent to pedestrians. All displays were placed at the front of the vehicle, just below the hood. Participants evaluated all images in all levels of the independent variable.

Neutral stimuli were excluded from the formal analysis because their displays were ambiguous and could not be categorized into crossing or staying signals. The neutral displays were, by design, open to interpretation and evaluating whether participants had accurately assessed their contents was impossible. Their exclusion helped strengthen the overall analysis by reducing confounding variables which may have impacted the power of the ANOVA and the validity of the results.

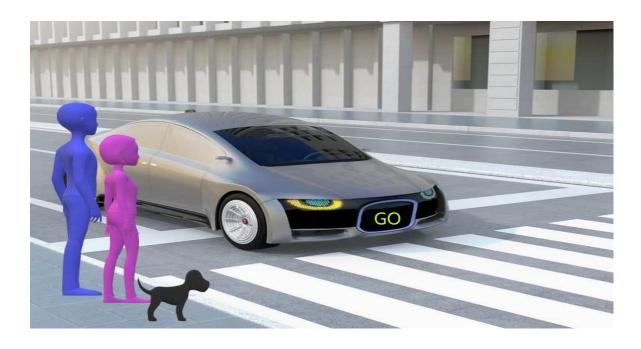


Figure 1. An example of an image used in the survey. This image is using the word "go" to indicate pedestrians can safely navigate the intersection.

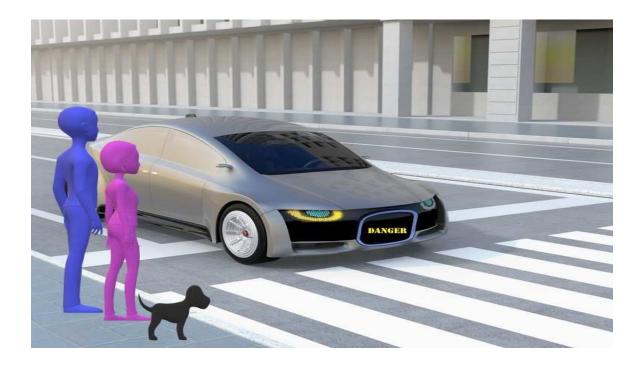


Figure 2. This example uses the written "danger" message to warn pedestrians against crossing.

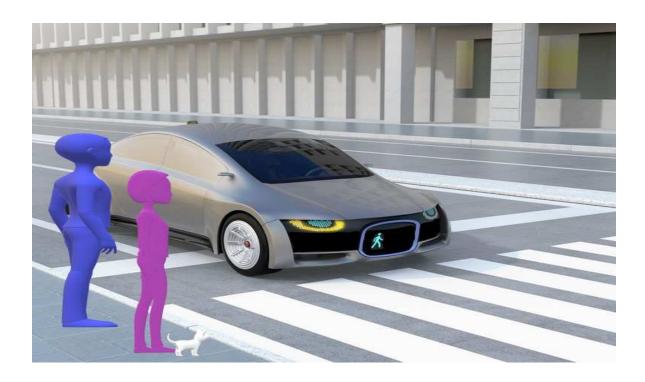


Figure 3. The display in this example utilizes a familiar pedestrian traffic signal to indicate it is safe to cross.

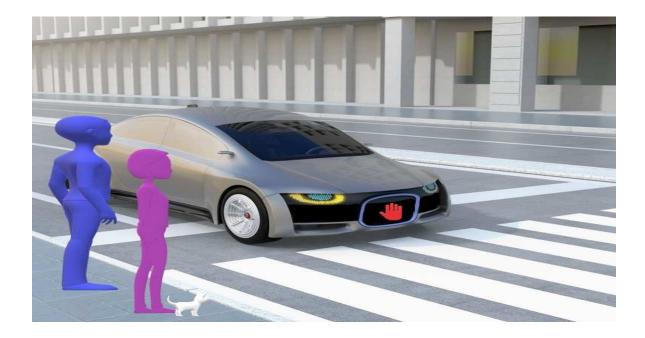


Figure 4. This display adopts the familiar red hand traffic signal. This traffic signal is used to warn pedestrians against crossing.

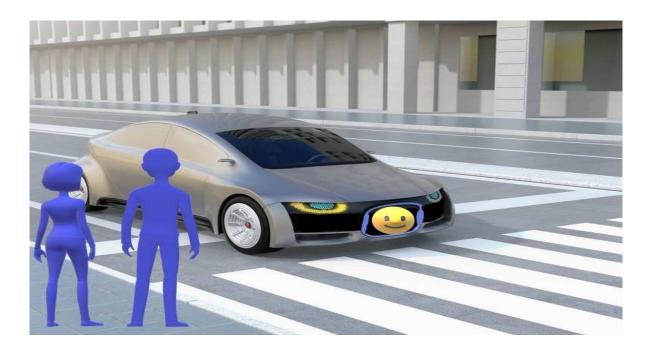


Figure 5. The display in this image uses a smiling face to communicate safety to pedestrians. This is an example of an anthropomorphic crossing signal.

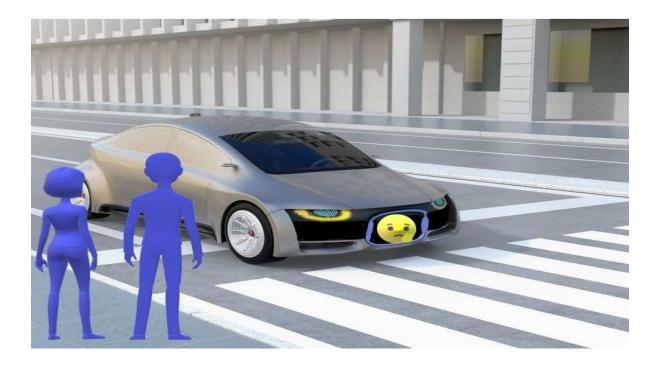


Figure 6. The display in this image uses a frown to warn pedestrians against crossing.

This is an example of an anthropomorphic signal used to communicate danger.

Procedure

The survey began by introducing a consent form replete with information concerning the study and participants' role within the research. Next, participants viewed photographs and illustrations of different proposed AV technologies. Some images were designed to alert participants to cross, while others were created to detract from crossing. These illustrations included different written prompts, traffic signals, and faces/smiles. Images were randomized throughout the survey. In each case, participants were asked to evaluate the images and identify whether they would be comfortable crossing the street in the presence of the vehicle at hand. Subject responses varied from "definitely yes", "probably yes", "probably not", and "definitely not". All images used the same setting, the same vehicle, and the same premise. The only aspects that were manipulated were the displays on the front of the vehicle, just below the hood. Traffic lights and external signals were omitted from images to reduce possible contamination from contextual cues. This was done to get as honest a response to proposed technologies as possible. All qualitative responses were then operationalized and recoded to reflect appreciable differences in perceptions with "definitely yes" and "probably yes" transformed to the number "1", and "probably not" and "definitely not" transformed to "0". The binary "1" and "0" reflected correct and incorrect responses, respectively. Technologies were then ranked based on this feedback in hopes of providing insight into their possible saliency and applicability in real-world settings.

RESULTS

The survey collected ordinal data and so a nonparametric Friedman's ANOVA by ranks was used for analysis. Responses were assessed for the number of correct interpretations of the various stimuli. Results showed significant differences between written, traffic, and

anthropomorphic signals, p < .001. Post hoc analysis with the Wilcoxon signed-rank tests was applied with a Bonferroni correction to account for differences between variables. Significance was set to p = 0.017 to account for the three conditions tested.

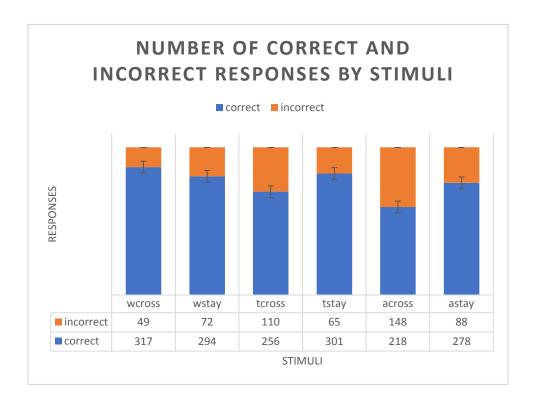


Figure 7. Number of correct and incorrect responses to written, traffic, and anthropomorphic display signals.

Crossing Signals

Post hoc analysis using the Wilcoxon signed-rank tests showed significant differences in crossing rates between written and anthropomorphic signals (p < 0.001) and between written and traffic signals (p = 0.001). Tests also concluded anthropomorphic crossing signals were significantly different from traffic signals (p = 0.001). These results confirm differences between written, traffic, and anthropomorphic displays in communicating safety to pedestrians.

Descriptive statistics suggested written displays were powerful tools for communicating AV intent to pedestrians. The "cross" signal text (M=3.01, SD=.828) was well understood as participants indicated they would most likely cross an intersection in the presence of a vehicle with such a message. The "go" (M=3.02, SD=.831) was also well received by participants. The most effective signal, on average, in the written level was the "safe" (M=3.30, SD=.853) signal. The animated hand traffic signal propositioning participants to cross was only marginally successful in communicating to pedestrians (M=2.63, SD=.823). The green (M=2.83, SD=.862) light was successful, because green traffic lights are associated with "go". The most well received display in the traffic category was the pedestrian crossing signal (M=3.22, SD=.902). The "thumbs up" display was successful in communicating safety as well (M=2.93, SD=.866). The anthropomorphic "happy face" (M=2.61, SD=.852) and "smile" (M=1.97, SD=.912) displays were among the least effective on average.

Stay Signals

Written and traffic signals indicating it was unsafe to cross the intersection were significantly different from one another (p = 0.002). However, written and anthropomorphic signals were not significant (p = 0.063). Interactions between traffic and anthropomorphic signals were similarly non-significant (p = 0.050).

Written signals were successful in relaying intent to participants. The "stay" signal text (M=1.63, SD=.846) was effective as participants correctly interpreted the message as indicating it was not safe to cross. The "stop" (M=1.66, SD=.849) and "danger" (M=1.43, SD .884) signals were also similarly salient. The red (M=1.65, SD= .797) light signal was successful in relaying intent, as was the pedestrian crossing signal (M=1.68, SD= .801). The anthropomorphic "thumbs

down" display conveyed danger (M=1.57, SD= .768) better than the "sad face" (M=1.73, SD=.820) and "frown" displays (M=1.65, SD=.883).

Neutral Signals

The neutral stimuli, were, as expected, inconclusive in establishing whether pedestrians could safely cross or not. The average for neutral written stimuli was M=1.96, the average for neutral traffic stimuli was M=1.94, and the average for neutral anthropomorphic stimuli was M=2.18.

DISCUSSION

The intended goal of the present study was to determine strategies for successfully communicating intent between AVs and pedestrians. To this effect, a survey was created comparing the efficacy of written displays, traffic signals, and anthropomorphic features. A Friedman's two-way nonparametric ANOVA was used to analyze findings from the survey. Post hoc results showed significant differences between written, traffic, and anthropomorphic displays. On average, written displays were most successful in communicating intent to participants. Participants correctly interpreted written stimuli for both safe and dangerous crossing conditions. Traffic signals were also interpreted well overall. On average, participants correctly surmised the intentions of vehicles displaying varying traffic signals. Anthropomorphic stimuli were least effective. Participants had varying levels of success evaluating stimuli like smiles, faces, etc. This may be because features like smiling, for example, are not closely associated with traditional motor vehicles, whereas key phrases and traffic signals have the potential to be far more intuitive.

One of the limitations to successfully determining effective strategies for communicating intent between AVs and pedestrians is the reliance on survey data. Surveys are effective tools, but they are limited in scope. Surveys cannot replicate the real-world settings in which AVs and pedestrians function in. Interpreting proposed solutions in the vacuum of a survey setting is wildly different from experiencing the same stimuli in person. Participants in this study were free to take their time in interpreting the various signals; something that would not be possible in a more realistic setting. There were no consequences for misinterpretation as there would be in the real-world where people are normally tasked with deciphering cues almost instantaneously lest they disrupt the flow of traffic and endanger themselves and others. In addition, signals may not be accurately represented in survey format. For example, some proposed strategies may effectively communicate with pedestrians, but may negatively impact other road users. Displays utilizing lights, signs, etc. have the potential to be disruptive to people not crossing streets and roads and may prompt them to make dangerous forays into traffic.

Interactions between AVs and pedestrians/cyclists are poorly researched domains of science. This is largely because autonomous vehicles are not commercially available at present. There is also a decided lack of relevant information from which to draw upon when studying the topic. The bulk of research in the field is carried out by automotive manufacturers and is unavailable to the public at large. This results in inconclusive conjectures into the efficacy of relevant interfaces. In addition, conclusions drawn from other branches of science, like human-computer interaction, are difficult to generalize to interactions between AVs-pedestrians. This is because the bulk of research in HCI centers on users and corresponding technologies. This is not the case with AVs and pedestrians, as pedestrian interactions with AVs are limited in scope.

Some of the figures in the survey illustrations were different across images. For example, some images had animated figures standing at different angles in relation to the autonomous vehicle than others did. This may have been a potential limitation as participants may have used the positions of animated figurines to decide whether it was safe to cross or not. This may have inadvertently influenced participant decisions to cross/stay.

AV-pedestrian interaction is a fascinating field which directly influences the development of autonomous driving technologies. Future studies should attempt to mimic real-life settings to provide generalizable results to the research community at large. One way of doing this would be to study signal detection in participants exposed to a variety of crossing/staying displays. Doing so would allow researchers to compare the efficacy of various displays while also identifying features which contribute to the saliency of different stimuli. This would help provide a strong foundation for building a better understanding of the steps necessary to facilitate the integration of AVs in daily life.

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APPENDIX I

DATA COLLECTED FEBRUARY-MARCH 2019

Survey Materials

Autonomous Vehicle Signaling Solutions

Start of Block: SURVEY INSTRUCTION

Q1

Welcome to the research study!

We are interested in understanding autonomous vehicle signaling. You will be presented with information relevant to signaling technologies and asked to answer some questions about it. Please be assured that your responses will be kept completely confidential.

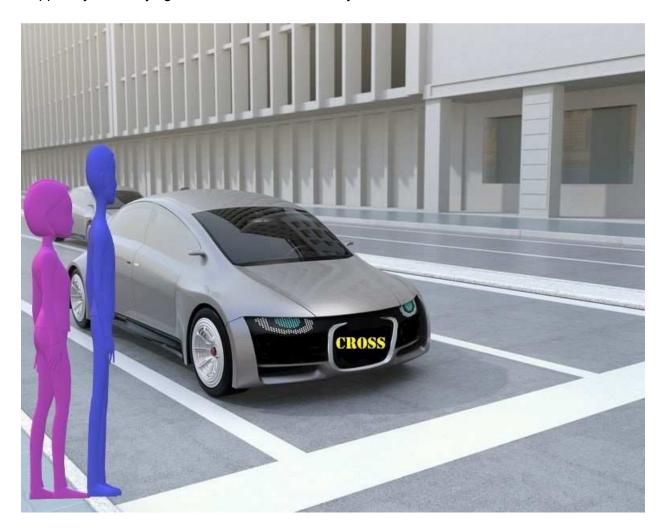
The study should take you around 15 minutes to complete, and you will receive \$0.25 for your participation via the mturk platform. Your participation in this research is voluntary. You have the right to withdraw at any point during the study, for any reason, and without any prejudice. If you would like to contact the Principal Investigator in the study to discuss this research, please e-mail Professor Nancy Cooke at nancy.cooke@asu.edu.

By clicking the button below, you acknowledge that your participation in the study is voluntary, you are 18 years of age, and that you are aware that you may choose to terminate your participation in the study at any time and for any reason.

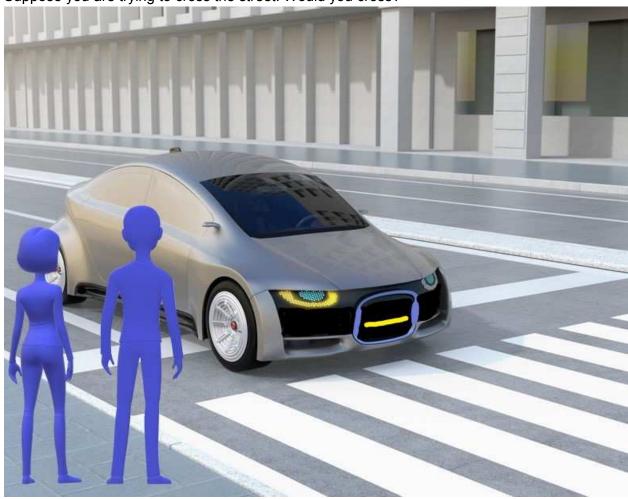
Please note that this survey will be best displayed on a laptop or desktop computer. Some features may be less compatible for use on a mobile device.

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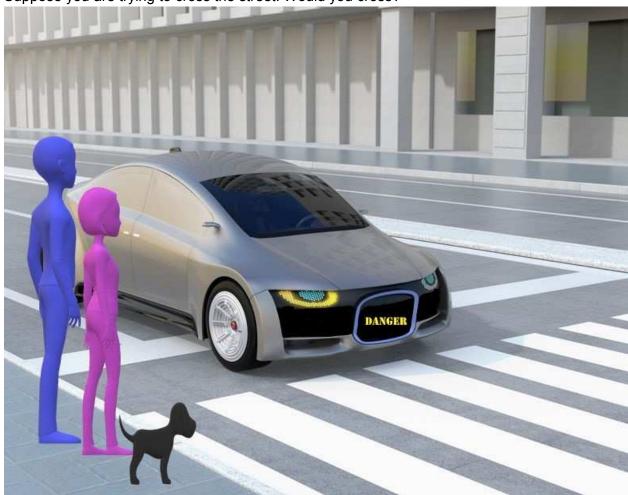
Q۷	4 You are
	O Male (1)
	○ Female (2)
	O Decline to specify (3)



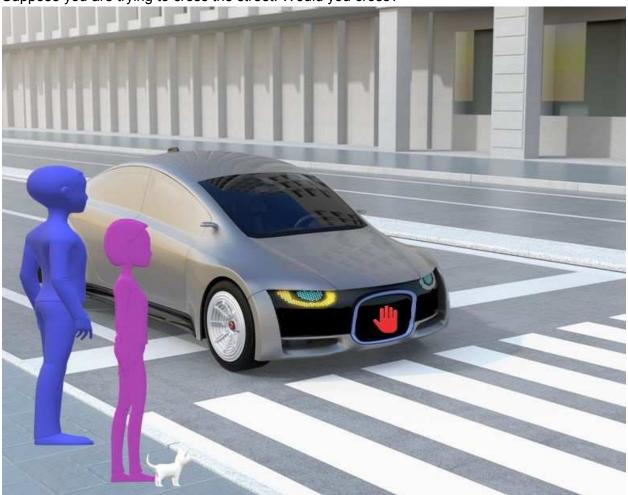
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



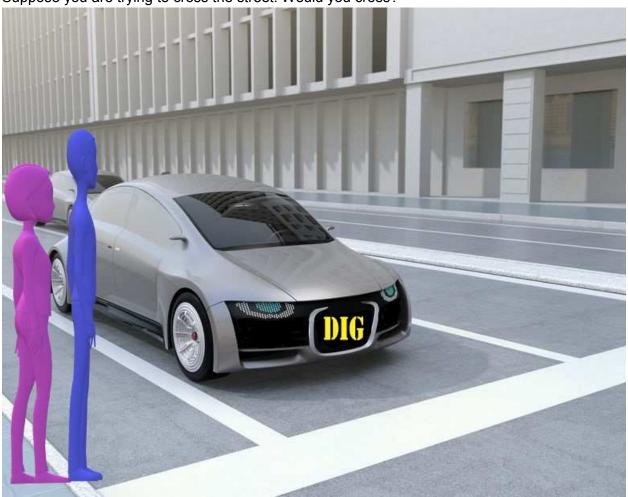
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



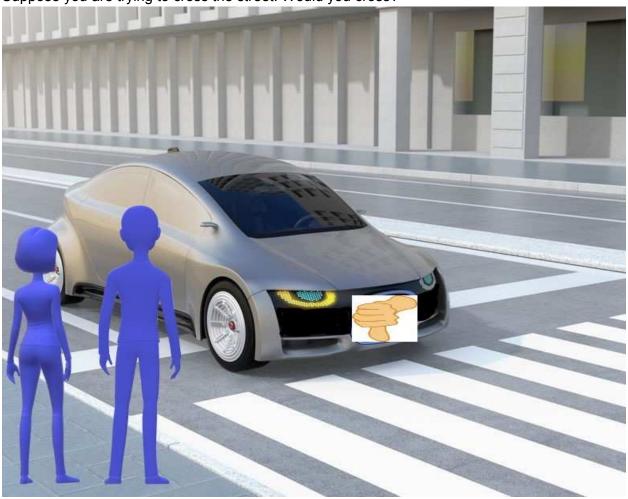
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



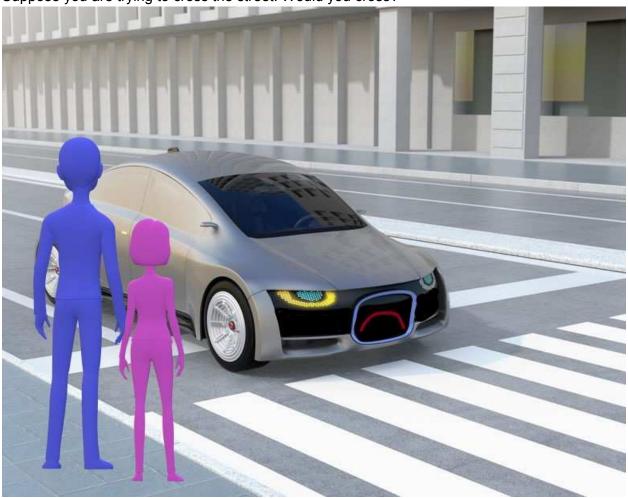
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



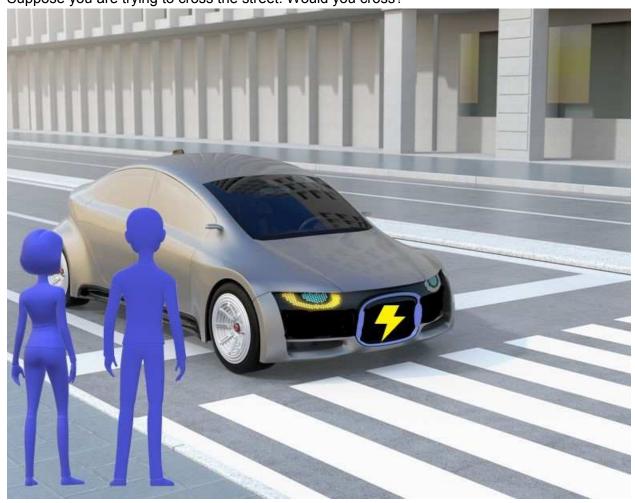
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



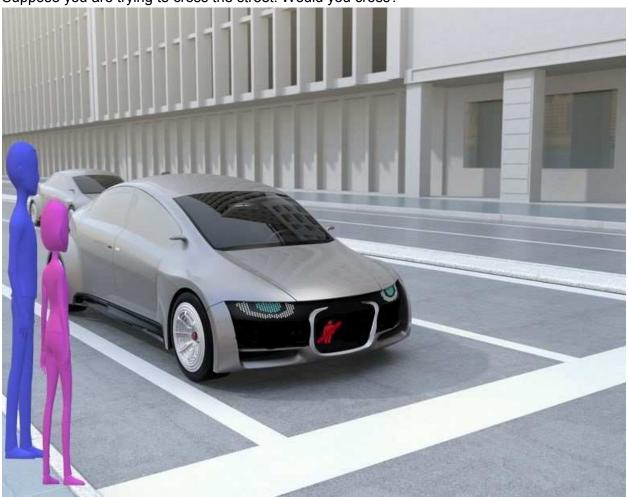
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



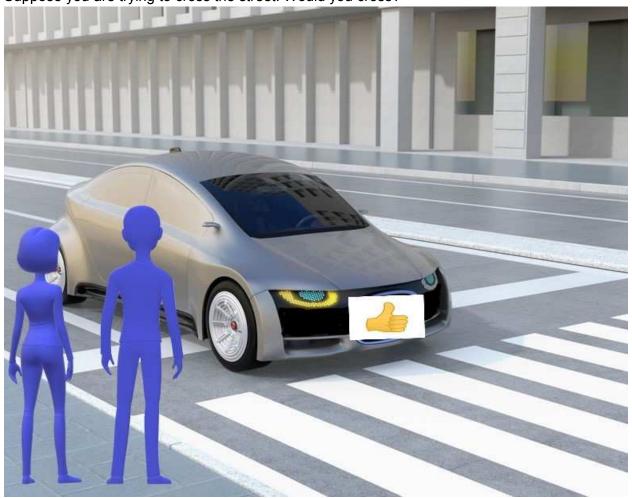
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



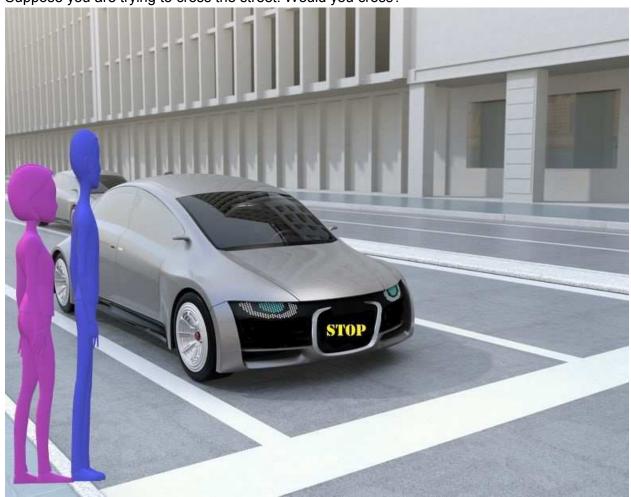
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



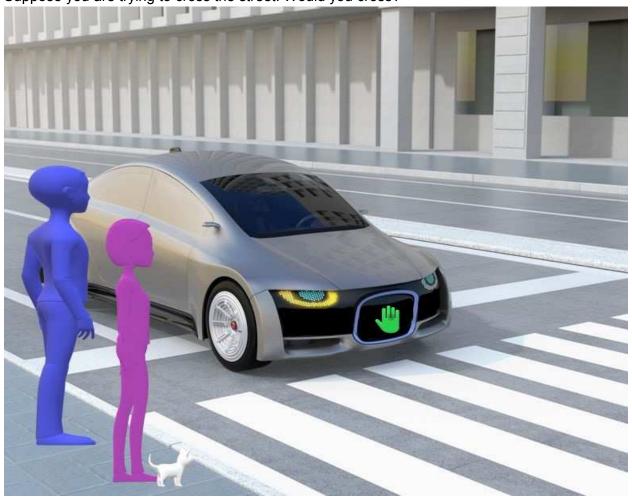
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



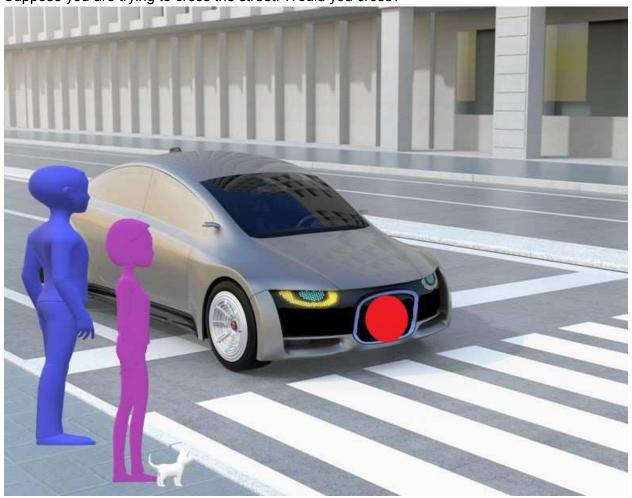
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



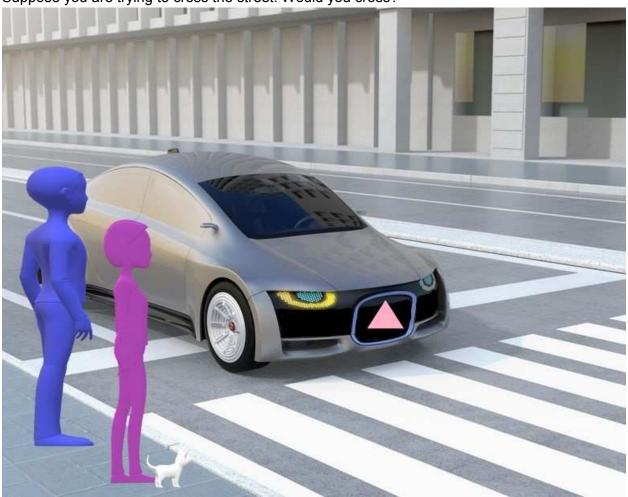
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



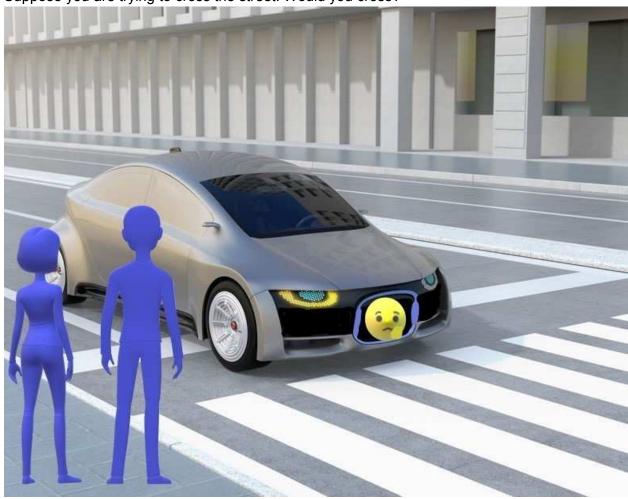
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



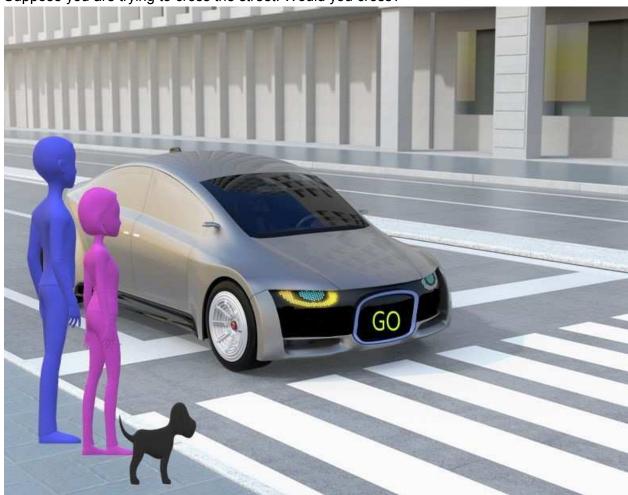
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



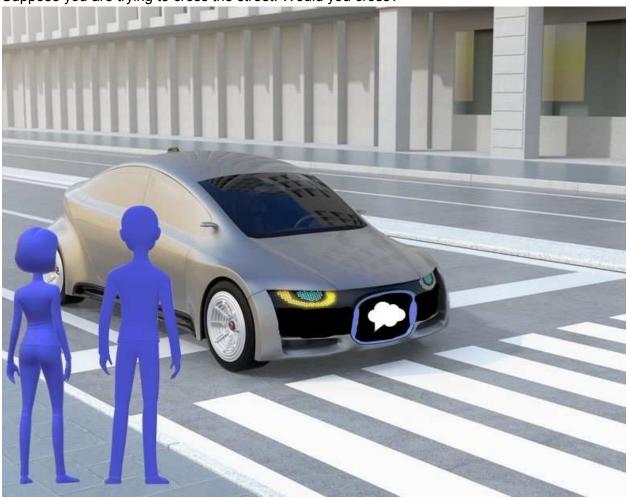
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



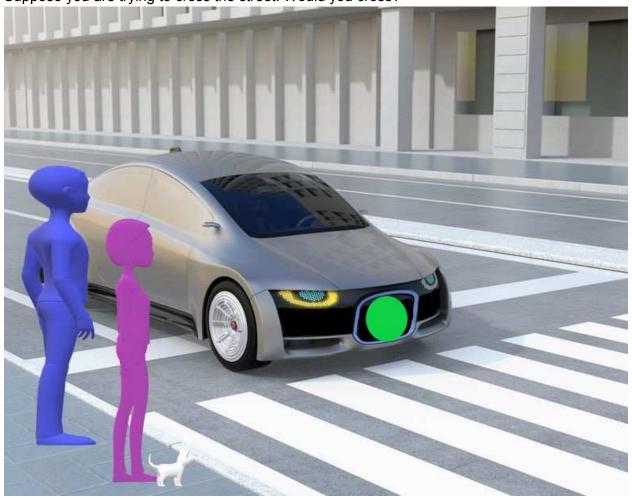
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



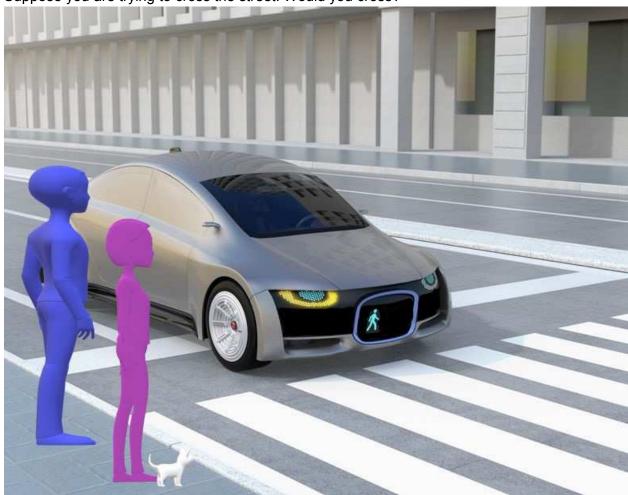
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



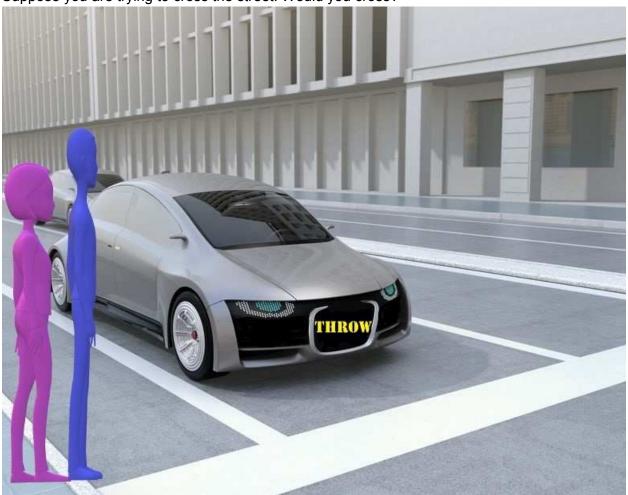
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



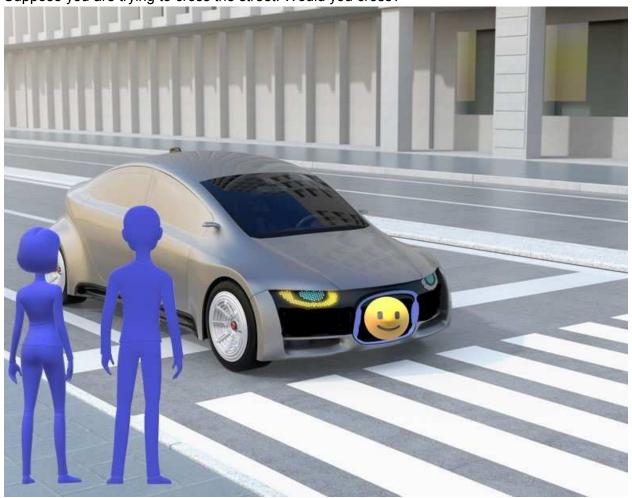
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



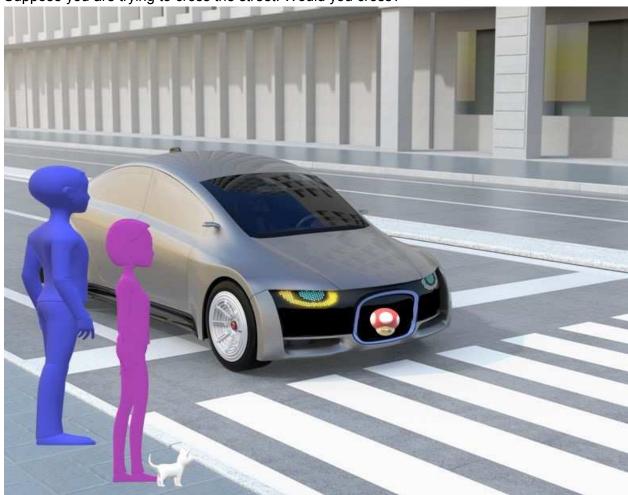
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



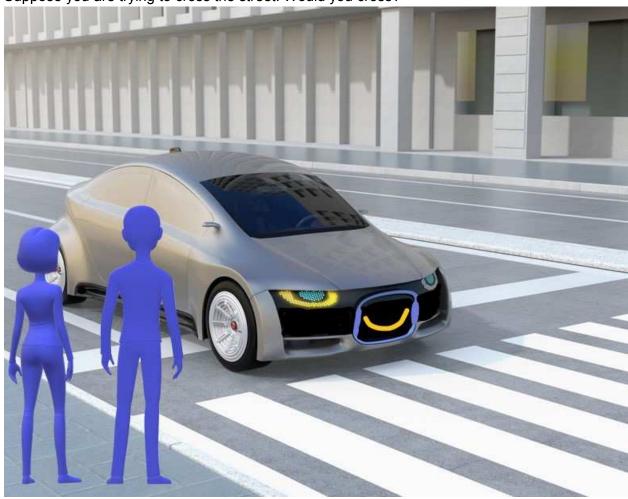
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



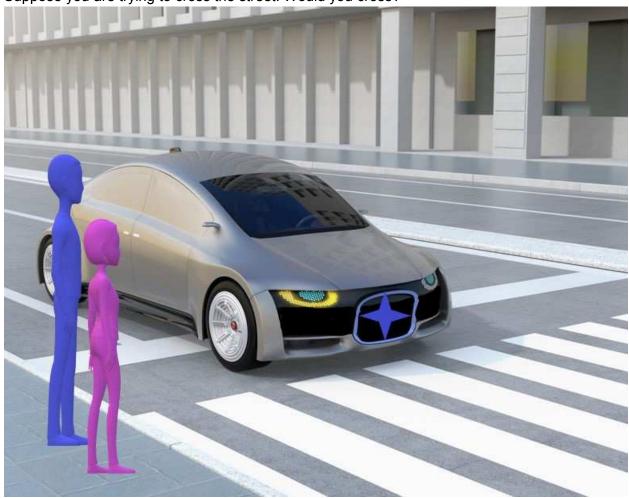
- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)



- O Definitely yes (1)
- O Probably yes (2)
- O Probably not (3)
- O Definitely not (4)