Autonomous Vehicles and Pedestrians: A Case Study of Human Computer Interaction

Subasish Das[1(✉)] and Hamsa Zubaidi[2]

[1] Texas A&M University, 3135 TAMU, College Station, TX 77843, USA
s-das@tti.tamu.edu
[2] Oregon State University, Corvallis, OR 97331, USA

Abstract. Understanding public attitudes, sentiments, and perceptions is a significant first step to the widespread acceptance of autonomous vehicles (AVs). In recent years, many studies been conducted in recent years examining the general perception of AVs. The implementation of AVs has potential challenges involving pedestrians and bicyclists that need special attention. The current study analyzes survey data obtained from BikePGH, a non-profit organization in Pittsburgh, Pennsylvania . This study applied multiple correspondence analysis (MCA) to explore response patterns among the participants. The findings of the survey reveal that certain groups of people are much more receptive to AV technology than others who are vehemently opposed to the introduction of AVs to the roadways. The findings indicate that participants who have real world experience with human-AV interactions have more positive expectations and a higher level of interest than participants with no previous experience. The authors expect that these findings will contribute greatly to the development of safety policies related AV and pedestrian interactions.

Keywords: Autonomous vehicle · Human computer interaction · Pedestrian · Correspondence analysis

1 Introduction

The introduction of autonomous vehicles (AVs) has earned global attention in recent years. New technologies have thoroughly transformed the transportation infrastructure. Fully automated AVs can reduce the number of crashes caused by human error and handle various traffic conditions without human feedback. Traffic congestion and air pollution can also be minimized by the introduction of AVs. In order to ensure that customers are aware if these many advantages, is necessary to consider end-users' awareness and attitude towards AVs.

The rate of non-motorized traffic fatalities is currently increasing. In 2016, 16 percent (5,987) of traffic fatalities were pedestrians and 2.3 percent (852) were bicyclists in the U.S. [33, 34]. A non-motorized roadway user (i.e., bicyclist or pedestrian) is more likely to severely injured or killed in road traffic crash. Studies have shown that AVs can increase roadways safety, but recent news reported a crash incident that resulted in a

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pedestrian fatality, in which an AV was in full automation mode. This event attracted worldwide media coverage, and it brought attention to safety concerns and research areas that need to be studied further, such as AV and non-motorized user (i.e., pedestrians and bicyclists on the roadways) interaction.

To visually explore complex patterns among the responses, we applied multiple correspondence analysis (MCA) to public survey data gathered by BikePGH in Pittsburgh, Pennsylvania [1]. In a complex questionnaire survey, traditional survey analysis techniques restrict the comprehension of event phenomena, and the interpretation and findings are limited to significant generalizations. The findings suggest that limiting the assessment to smaller clusters greatly benefits the ability to understand and interpret the participants' response patterns towards AVs, based on their previous interaction level with AVs as pedestrians.

2 Literature Review

On public and private roads in multiple countries, large-scale testing of AVs is currently being introduced. However, these innovations are not necessarily accepted by all. technologies need to tackle technological challenges as well as social barriers in order to successfully join the marketplace. Several studies have previously analyzed consumers' views and public opinions about the potential implementation of AV technologies [17, 20, 22, 24, 25].

Schoettle and Sivak [38] used survey analysis to study public opinion about the use of AVs in the U.S., the U.K., and Australia. The findings suggested that women show more concern about AV technologies than men. Furthermore, a majority of the respondents indicated interest in possessing a vehicle with this technology, but a majority of them were not willing to pay extra costs. Howard and Dai [26] conducted a case study utilizing the responses of 107 AV users in Berkeley, California to assess public attitudes regarding AVs. An assessment was conducted to determine which vehicle features people liked and disliked, and the participants were asked to explain how they envisioned the implementation of the technology. The potential safety improvements, the ease of finding parking spots, and the ability to multitask while driving were all features that were associated with positive attitudes. In contrast, the traits for which people expressed concern included potential liability, the vehicle cost, and the possibility of losing control. The findings showed that women were less concerned with liability and more concerned with control than men. Choi et al. [9] studied the experience of users adopting AVs and explored which factors could promote people's trust in AVs. The study found that perceived trust and utility are significant factors that affect people's likelihood of using AVs. Furthermore, the findings showed that three structures had positive impacts on trust: technical competence, system transparency, and situation management. In another study, Kyriakidis et al. [30] analyzed user willingness to own AVs with different automation levels. An internet-based survey with 63 questions was used in this study; it produced 5,000 responses from 109 countries. Furthermore, participants were primarily concerned with hacking or software misuse, legal problems, and safety.

Bansal et al. [7] introduced a new simulation-driven fleet evolution system to forecast the long-term (year 2015–2045) adoption levels of AV technology in America based on eight scenarios created to encompass 0%, 5%, and 10% annual increments in Americans' willingness to pay (WTP); 5% and 10% annual drops in technology prices; as well as new or changing government regulations. Krueger et al. [29] studied the travel behavior effects of AVs in order to advance future research. They identified features of consumers who are likely to adopt AV technology and assessed their willingness to pay additional costs for various service enhancements. The study findings revealed that service features such as travel cost, travel time, and waiting time are important factors of AV use and the users' acceptance of them. The adoption and acceptance levels may vary among people in different demographic groups. For example, young people and multimodal travelers are more likely to use AVs.

Daziano et al. [14] used data from a national online panel of 1,260 individuals. The study is designed in the setup of a discrete choice experiment for vehicle purchases based on energy efficiency and autonomous characteristics. The aim of their research was to find a proper estimate of the willingness of individuals to pay for AVs. The aggregate findings of their surveys show that the average household is prepared "to pay approximately $3,500 for partial automation and $4,900 for full automation." Menon [32] analyzed the future market segments of AV customers and disclosed the factors affecting AV adoption or non-adoption. The results revealed that the impact of giving up household vehicles varies among households with single or multiple vehicles as well as households with various triggers including socio demographics, vehicle purchase histories, and current travel characteristics.

The responses from a national survey of 1,765 adults in the U.S. were examined by Lee et al. [31] to classify the key factors of AV acceptance and to assess how age and other attributes are related to AV perceptions and attitudes. The findings of the study revealed age's negative effects on perceptions of AVs, interest in using them, and behavioral plans to use them when the technology is available. Furthermore, experiential characteristics related to age, such as knowledge of, experience level, and general trust toward technology, all had a significant impact on people's feelings towards AVs.

To assess their perspectives on AVs and related decisions, Bansal and Kockelman [5] surveyed 1,088 people in Texas and considered their demographics, travel patterns, crash histories, and built-environment attributes. The results demonstrate that older drivers and those with more driving experience are less willing to pay (WTP) for new vehicle technologies like AVs. Bansal and Kockelman [6] carried out a follow-up study using an internet-based survey that asked 347 Austinites about their opinions on smart-car technologies. The findings concluded that the participants consider less crashes to be the main benefit of self-driving cars and possible equipment failure to be their primary concern. Hulse et al. [27] conducted a survey of nearly 1,000 individuals to study their opinions of AVs regarding safety and acceptance. The results revealed that AVs are viewed as 'somewhat low risk' and there was not much resistance to their use on public roads. AVs were also perceived as having more risks than autonomous trains. It was found that gender, age, and risk-taking characteristics had various relationships with the perceived risk of various vehicle types and general opinions of AVs. For instance, men and younger adults showed a greater level of acceptance.

Canis [8] conducted a survey and found that 30 percent the respondents demonstrated unwillingness in purchasing an AV. The analysis also found that more than 50% of U.S.

drivers "feel less safe at the prospect of sharing the road with a self-driving vehicle." Das et al. [2] analyzed the attitudes of people towards AVs and the present polarities about content and automation levels used two natural language processing (NLP) tools to conduct knowledge discovery from a bag of approximately seven million words using YouTube video comments. The findings showed that the public is interacting with AV technologies more now than in the past; they also showed that as the degree of automation increases, so does the potential perception of safety. Finally, they concluded that there are more widespread positive feelings about AVs than negative, uncertain, or litigious feelings. Penmetsa et al. [37] assessed survey data obtained from BikePGH and found that respondents with previous experience of direct AV interaction reported significantly higher perceptions of their safety benefits than respondents without any experience of AV interaction.

The literature review shows several gaps. First, user attitudes are not reliant on the future safe implementation of AVs. Furthermore, the previous AV interaction level of participants is unknown in a majority of the studies. Another limitation is that not many studies have explored non-motorist perception of AVs. Additionally, traditional survey analysis approaches have limited interpretation abilities for co-occurrences of the responses. The present study provides an acceptable data analysis method that can recognize trends and correlations from a complex sample to clarify the attitude of roadway users towards the adoption of AVs.

3 Data Description

3.1 Survey Design and Participants

According to the first edition of the Highway Safety Manual (HSM), approximately 94 percent of collisions occur due to human errors [36]. AV companies expect that the AV technologies could eliminate the human error component of the driving tasks and therefore, greatly minimize these crashes. AVs offer many potential advantages independent of the automation modes (partial to full automation), such as minimizing roadway crashes and fatalities, reducing traffic congestion, and promoting mobility [35, 36]. However, AVs can also cause safety and infrastructure issues that state Department of Transportation (DOT) authorities must solve. DOTs must determine if a stable driving environment can be ensured with the current standards and methods of vehicle testing. Furthermore, AV interactions with other road users must be addressed. Infrastructure changes may be required for AV implementation, and policymakers will need to determine which changes they should pursue, while still catering to the needs of conventional vehicles which will continue to be used for decades. However, several regulating organizations do not have comprehensive plans that are readily available to set specific targets regarding the introduction of AVs to roadways [28].

AV firms have tested AVs in major cities since September 2016. In 2017, ten AV proving grounds were assigned by the United States Department of Transportation (USDOT) to promote testing of AV technologies; one of these testing grounds was located in Pittsburgh, PA. In early 2017, BikePGH developed a survey to gather information about how BikePGH donor-members as well as Pittsburgh residents at large feel about sharing the road with AVs as a non-motorized roadway user (i.e., bicyclist or pedestrian).

This survey aimed to help policymakers comprehend the complexity of futures involving AV technologies by demonstrating how AVs can bring introduce marketplace models to cities and town centers. The survey was conducted in two parts. In the first stage, the survey only included Bike PGH donor-members; this stage was conducted via email and it yielded 321 responses (out of 2,900). The second stage encouraged the public to participate by publishing it on the BikePGH website and promoting it via social media and several news articles. This stage produced 798 responses (mostly from Pittsburg residents for a combined total of 1,119 responses. The major questions from the survey are listed below.

- *InteractPedestrian:* Real-life interaction with AVs?
- *BikePghPosition:* Opinion on BikePGH's position on AVs?
- *CircumstancesCoded:* Six categories: AV Safer, Cautious about AV, Negative about AV, No Difference, No Experience, and Others.
- *SafetyHuman:* Feel safe with human driven vehicles on road?
- *SafetyAV:* Feel safe with AVs on road?
- *AVSafetyPotential:* AV safe enough?
- *RegulationTesting:* Regulation on AV testing?
- *RegulationSpeed:* Lower speed limit on roads that allow AVs?
- *RegulationSchoolZone:* Disallow AVs on school zones?
- *RegulationShareData:* Share AV movement data with public or regulatory agencies?
- *FeelingsProvingGround:* Use Pittsburgh's public streets as a proving ground for AVs?
- *AdvocacyIssues:* Should it be an advocacy issue for BikePGH?
- *PayingAttentionAV:* Pay attention AV news?
- *FamiliarityTechnoology:* Familiarity with AV technology?

3.2 Exploratory Data Analysis

The final dataset contains 321 responses from the BikePGH members (BPG) and 793 responses from the general public (Public) for a total of 1,114 respondents. The current analysis is limited to human-computer interaction framework for pedestrians. Table 1 lists attribute distribution by variables and results of chi-square test. The lower p-values ($p < 0.05$) from the chi-square tests indicate that some of the variables are significantly different for three types of participants based on their prior human computer interaction regarding AVs as pedestrians: yes (406 participants), no (599 participants), and not sure (109 participants).

The circumstances are coded into six categories: *AV Safer, Cautious about AV, Negative about AV, No Difference, No Experience, and Others.* Around 37% percent of the survey participants have prior experience of AV circumstances. the response patterns. Approximately 5.17% of the survey participants with prior interactions with AVs feel AV safer. This percentage is lower in other two groups with no (or not sure) prior experience with AVs. The response regarding *SafetyAV* (5 as very safe) is also higher in percentage in the responses of the participants with prior experience with AVs. This group also indicates they are mostly in favor of considering Pittsburgh as the proving ground of AVs. Two other information are important in this analysis: 1) familiarity with technology (*FamiliarityTechnoology*), and 2) paying attention to AVs (*PayingAttentionAV*).

Table 1. Compare groups

Questions	Yes	No	Not sure	p-val	Questions	Yes	No	Not sure	p-val
	(N = 406)	(N = 599)	(N = 109)			(N = 406)	(N = 599)	(N = 109)	
BikePghPosition				< 0.001	*CircumstancesCoded*				
Actively oppose	4.93%	6.68%	5.50%		AV Safer	5.17%	1.34%	1.83%	
Actively support	55.40%	38.90%	36.70%		Cautious about AV	11.60%	2.50%	6.42%	
Neither support nor oppose	31.00%	42.90%	45.90%		Negative about AV	5.91%	2.00%	0.00%	
No opinion	8.62%	11.50%	11.90%		No difference	60.10%	21.70%	23.90%	
SafetyHuman					No experience	14.30%	69.60%	65.10%	
1	5.17%	5.01%	7.34%		Others	2.96%	2.84%	2.75%	
2	30.30%	26.90%	30.30%		*SafetyAV*				< 0.001
3	40.90%	40.40%	40.40%		1	3.94%	5.84%	6.42%	
4	21.40%	22.40%	16.50%		2	9.11%	9.52%	11.00%	
5	2.22%	4.17%	4.59%		3	21.40%	24.20%	25.70%	
No experience	0.00%	1.17%	0.92%		4	39.40%	29.00%	30.30%	
AVSafetyPotential				< 0.001	5	25.10%	14.50%	16.50%	
1: Yes	73.60%	60.30%	56.90%		No experience	0.99%	16.90%	10.10%	
2: No	4.43%	7.68%	8.26%		*RegulationTesting*				0.001
3: Not sure	21.90%	32.10%	34.90%		1: Yes	64.50%	75.10%	69.70%	

(continued)

Table 1. (*continued*)

Questions	Yes	No	Not sure	p-val	Questions	Yes	No	Not sure	p-val
RegulationSpeed				< 0.001	2: No	16.50%	8.68%	11.00%	
1: Yes	44.60%	54.90%	54.10%		3: Not sure	19.00%	16.20%	19.30%	
2: No	38.20%	25.00%	29.40%		*RegulationSchoolZone*				< 0.001
3: Not sure	17.20%	20.00%	16.50%		1: Yes	18.50%	27.90%	30.30%	
RegulationShareData				0.873	2: No	56.90%	41.60%	42.20%	
1: Yes	71.20%	71.60%	73.40%		3: Not sure	24.60%	30.60%	27.50%	
2: No	13.50%	12.00%	10.10%		*FeelingsProvingGround*				< 0.001
3: Not sure	15.30%	16.40%	16.50%		1: Not at all	6.16%	8.51%	9.17%	
AdvocacyIssues					2: Little	7.39%	9.02%	12.80%	
1: Not at all	5.91%	4.01%	2.75%		3: Some	11.80%	14.40%	11.00%	
2: Little	16.30%	13.70%	13.80%		4: Moderate	14.30%	23.90%	22.90%	
3: Some	38.20%	41.90%	40.40%		5: A lot	60.30%	44.20%	44.00%	
4: Moderate	33.50%	34.90%	36.70%		*PayingAttentionAV*				
5: A lot	6.16%	5.51%	6.42%		1: Not at all	0.99%	1.50%	1.83%	
FamiliarityTechnoology				< 0.001	2: Little	6.40%	10.50%	11.90%	
1: Not at all	2.96%	8.68%	6.42%		3: Some	24.90%	32.90%	33.90%	
2: Little	20.20%	20.00%	30.30%		4: Moderate	33.50%	33.10%	33.00%	
3: Some	39.70%	46.10%	35.80%		5: A lot	34.20%	22.00%	19.30%	
4: Moderate	23.60%	17.90%	20.20%		*Group*				0.047
5: A lot	13.50%	7.35%	7.34%		BPG	32.50%	25.70%	32.10%	
					Public	67.50%	74.30%	67.90%	

The group with prior human-computer interaction with AVs shows that they are more familiar with technology and they pay attention to AVs than the other two groups.

4 Methodology

4.1 Multiple Correspondence Analysis

Multiple Correspondence Analysis (MCA), a dimension reduction method, mandates the formation of a matrix based on pairwise cross-tabulation of explanatory and response variables but does not differentiate between the two variable types. For instance, 1114 × 10 would be the dimension of the used data if the number of total survey respondents was 1114 and there were 10 questions analyzed in the survey. For a categorical or qualitative variable table with the dimensions 1114 × 10, MCA can be described by taking an individual record (in row), i [i = 1 to 1114], where the 10 categorical variables are represented by 24 columns that have different sizes for the categories.

Consider P as the total variables (i.e., columns), and I as the total responses (i.e., rows). This will produce a matrix of $I \times P$. If L_p is the total attributes for variable p, then the sum of the categories for all variables is, $L = \int_{p=1}^{P} L_p$. This will produce another matrix $I \times L$, in which each variable will comprise multiple columns to display all of their possible categorical values. The cloud of categories is known as a weighted combination of J points. Category j is shown by a point denoted by Cj with the weight of nj. For each of variables, the total of the weights of category points is n. Following this, for the entire set J, the sum is nP. The relative weight wj for point Cj is $wj = nj/(nP) = fj/P$. The total of the relative weights for category points is $1/P$; thus, the sum of the entire set is 1 [36]. $w_j = \frac{n_j}{nP} = \frac{f_j}{P}$ with $\int j \in J_q w_j = \frac{1}{P}$ and $\int j \in J w_j = 1$. Here, $n_j n_j$ is the number of individual points that have both categories k and k'. The squared distance from Cj to Cj' is shown in Eq. 1 [36]:

$$\left(C^j C^{j'}\right)^2 = \frac{n_j + n_{j'} - 2n_{jj'}}{n_j n_{j'}/n} \tag{1}$$

In Eq. 1, $n_j + n_{j'} - 2n_{jj'}$ is the number of individual records associated with either j or j$^{'}$. For variables p and p', the denominator is the familiar "theoretical frequency" for the cell $\left(j, j'\right)$ of the $Jp \times Jp'$ two-way table. Other MCA frameworks have been created with similar goals [21, 23]. Several recent studies have applied MCA in transportation research [3, 4, 10–13, 15, 16, 18, 19].

5 Results and Discussion

The variables with low p-values (less than 0.10, see Table 1) indicate that the groups (pedestrian-AV interaction = yes vs. pedestrian-AV interaction = no) are significantly different in attitude towards AVs for the associated attributes. The variables that show significant differences among these three types of participants based on their prior human computer interactions regarding AVs include *BikePghPoisition, SafetyHuman, AVSafetyPotential, RegulationSpeed, AdvocacyIssues, FamiliarityTechnology, CircumstancesCoded, SafetyAV, RegulationTesting, RegulationSchool-Zone, FeelingsProvingGround, and PayingAttentionAV*. To conduct the MCA analysis, we considered seven variables (*SafetyHuman, AVSafetyPotential, FamiliarityTechnology, CircumstancesCoded, SafetyAV, PayingAttentionAV, and InteractPedestrian*) for analysis to identify the clusters based on their prior interactions with AVs as pedestrians.

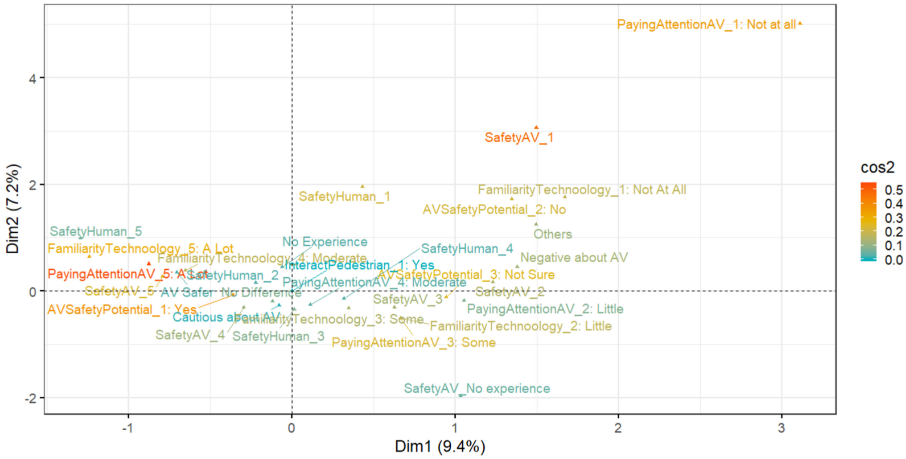

Fig. 1. MCA plot (pedestrian interaction group: yes)

Figure 1 to Fig. 3 illustrate the MCA plots by three groups: group 1 (yes), group 2 (no), and group 3 (not sure). The first two axes of the MCA plot explain nearly 20% of total inertia. Due to the presence of large number of attributes, MCA plots may sometimes become noisy. The closer the locations of the attributes in the MCA plot, the closer the associations between these attributes. Figure 1 (MCA plot for group 1) shows that the responses ‘a lot’ for two variable familiarity with technology (*FamiliarityTechnology*) and paying attention to AV (*PayingAttentionAV*) are closer to other relevant responses. The negative responses regarding AVs (*SafetyAV* as 1 or very low, *PayingAttentionAV* as ‘not at all’, *FamiliarityTechnology* as ’not at all’) are not in the close proximity of other responses that are more positive towards AVs. On the other hand, Fig. 2 and Fig. 3 show MCA plots for other two groups (group 2 and group 3). The negative responses towards AVs are clustered in a group for group 3. Similarly, *PayingAttentionAV* as ‘a lot’, and *FamiliarityTechnology* as ‘a lot’ are not in the close proximity of other responses that are positive towards AVs in group 2.

The overall finding shows that participants of similar mindset are clustered in groups. For example, participants with negative views are in closer proximity for a cluster and same for the participants with positive views. The parameter squared cosine ($\cos^2$) indicates the degree of association between variable attributes and a dimension or axis. If a variable attribute is well represented by two dimensions in a plane, the sum of the $\cos^2$ will be approximately one. Sometimes, n-dimensional display is required if the

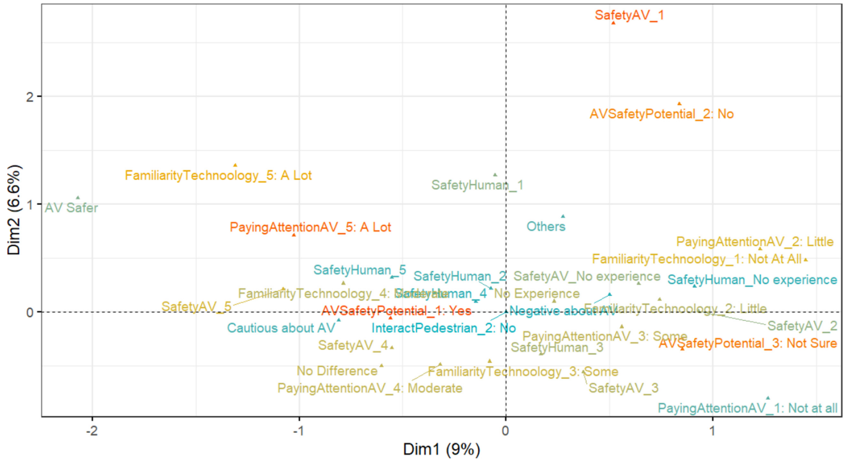

Fig. 2. MCA plot (pedestrian interaction group: no)

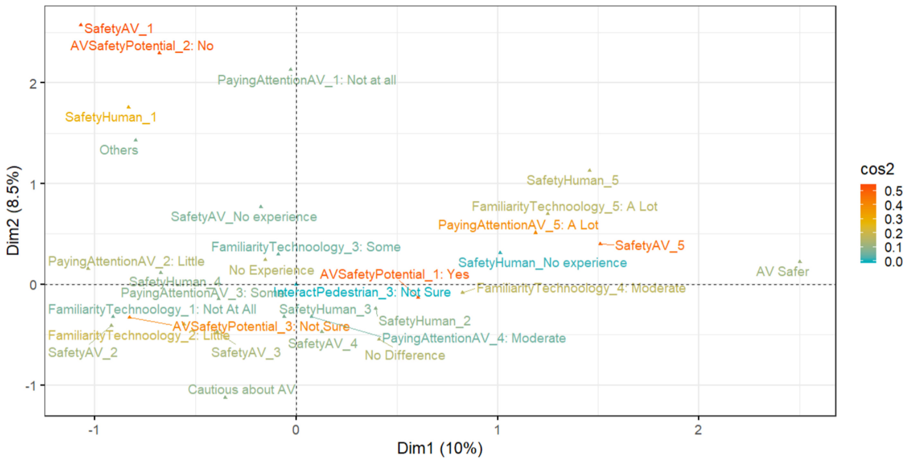

Fig. 3. MCA plot (pedestrian interaction group: not sure)

inertia or variance of the first two dimensions are inadequate. Table 2 lists the $\cos^2$ values for axis 1 (dimension 1) and axis 2 (dimension 2) for three groups. For each attribute, ranks are provided based on total $\cos^2$ values for both axes. The top 10 ranks for each group are colored in red. For group 1, the attribute that can explain more in both axes is *PayingAttentionAV* as 'a lot'. For group 2, *AVSafetyPotential* as 'yes', and *SafetyAV* as '1 (very low)' are the top two attributes. *SafetyAV* as '1 (very low)' is also a top attribute for group 3. The rank distribution also indicates that group 1 participants are more positive towards AVs compared to other two groups.

Table 2. Contributions by attributes

ID	Attribute	Yes				No				Not Sure			
		Dim 1	Dim 2	Tot	Rank	Dim 1	Dim 2	Tot	Rank	Dim 1	Dim 2	Tot	Rank
1	AVSafetyPotential: Yes	0.366	0.013	0.379	3	0.475	0.006	0.480	1	0.336	0.063	0.399	6
2	AVSafetyPotential: No	0.084	0.137	0.221	9	0.058	0.310	0.368	5	0.124	0.039	0.162	11
3	AVSafetyPotential: Not Sure	0.250	0.004	0.254	6	0.342	0.057	0.399	4	0.000	0.085	0.085	23
4	PayingAttentionAV_1: Not at all	0.096	0.251	0.347	4	0.024	0.010	0.034	24	0.003	0.066	0.069	26
5	PayingAttentionAV_2: Little	0.076	0.002	0.078	21	0.177	0.040	0.217	8	0.076	0.011	0.087	22
6	PayingAttentionAV_3: Some	0.145	0.088	0.233	8	0.152	0.009	0.162	14	0.104	0.021	0.125	16
7	PayingAttentionAV_4: Moderate	0.006	0.032	0.038	25	0.050	0.116	0.167	13	0.172	0.002	0.174	9
8	PayingAttentionAV_5: A Lot	0.401	0.136	0.536	1	0.298	0.144	0.441	3	0.484	0.023	0.507	3
9	SafetyAV_1	0.092	0.385	0.476	2	0.017	0.447	0.463	2	0.078	0.456	0.534	1
10	SafetyAV_2	0.151	0.003	0.154	14	0.091	0.000	0.091	21	0.145	0.003	0.148	13
11	SafetyAV_3	0.107	0.025	0.132	17	0.044	0.101	0.145	16	0.053	0.094	0.147	14
12	SafetyAV_4	0.057	0.062	0.119	18	0.125	0.045	0.170	12	0.057	0.007	0.064	27
13	SafetyAV_5	0.211	0.026	0.237	7	0.197	0.008	0.205	9	0.041	0.474	0.515	2
14	SafetyAV_No experience	0.011	0.038	0.049	24	0.083	0.014	0.097	20	0.089	0.002	0.092	21
15	Circums: AV Safer	0.027	0.006	0.034	27	0.058	0.015	0.073	23	0.009	0.001	0.010	30
16	Circums: Cautious about AV	0.001	0.010	0.010	30	0.017	0.000	0.017	28	0.102	0.061	0.163	10
17	Circums: Negative about AV	0.120	0.013	0.132	16	0.005	0.001	0.006	30	0.009	0.086	0.095	19
18	Circums: No Difference	0.021	0.055	0.076	22	0.100	0.070	0.170	11	0.134	0.068	0.203	8
19	Circums: No Experience	0.001	0.034	0.035	26	0.122	0.022	0.144	17	0.053	0.078	0.131	15
20	Circums: Others	0.068	0.048	0.116	19	0.002	0.023	0.025	25	0.003	0.052	0.054	28
21	SafetyHuman_1	0.010	0.210	0.220	10	0.000	0.085	0.085	22	0.044	0.112	0.156	12
22	SafetyHuman_2	0.021	0.011	0.032	29	0.002	0.017	0.019	26	0.018	0.058	0.076	24
23	SafetyHuman_3	0.000	0.082	0.083	20	0.019	0.105	0.125	19	0.055	0.244	0.299	7
24	SafetyHuman_4	0.027	0.005	0.032	28	0.006	0.003	0.009	29	0.002	0.070	0.072	25
25	SafetyHuman_5	0.038	0.022	0.060	23	0.013	0.004	0.018	27	0.117	0.001	0.118	17
26	FamiliarityTechnoology_1: Not at All	0.085	0.095	0.180	12	0.199	0.022	0.221	7	0.451	0.032	0.482	4
27	FamiliarityTechnoology_2: Little	0.113	0.068	0.180	11	0.138	0.003	0.141	18	0.007	0.096	0.103	18
28	FamiliarityTechnoology_3: Some	0.080	0.069	0.149	15	0.006	0.181	0.186	10	0.068	0.025	0.093	20
29	FamiliarityTechnoology_4: Moderate	0.132	0.048	0.179	13	0.135	0.015	0.150	15	0.004	0.049	0.053	29
30	FamiliarityTechnoology_5: A Lot	0.241	0.066	0.307	5	0.136	0.146	0.282	6	0.367	0.058	0.424	5

6 Conclusions

For the comprehensive implementation of AVs, it is crucial to gather response from end-users and understand acceptance tolerances. Furthermore, understanding public perception of emerging technologies like AVs is critical for public policy. Major AV companies expect that AVs will be sufficiently trustworthy and economical to replace a majority of human driving by 2030, giving roadway users independent mobility [3]. As AVs continue to develop rapidly, there is an increasing need to control the adoption of these technologies in the real-world roadway environment.

Due to their health and environmental benefits, non-motorized modes of transport such as walking has become popular. Unfortunately, the high exposure of pedestrians in urban areas might have contributed to the sharp increase in pedestrian crashes in the recent years. Due to the high exposure of pedestrians and rapid growth of AV testbeds, it is critical to comprehend the public perception towards pedestrian and AV interactions.

We analyzed participants' attitudes towards AVs and considered their human AV interaction and gathered findings to inform policy development for AV adoption. We found that pedestrians with previous AV interactions think AVs are safer than human drivers and they recognize the potential safety benefits of AVs. The survey also found that participants without previous AV experience believe that Pittsburgh streets are safe with human drivers. The study's findings show that prior experience and knowledge of AVs are associated with more positive opinions and perceptions. This provides evidence to the value of AV demonstration projects that offer non-motorized roadway users with the opportunity to interact with AVs.

Our study has several limitations. First, only a limited region was included in the survey. Additionally, detailed information about the AV interactions within this survey were not publicly available for use. Further studies could perform text mining on these narratives to help identify the missing link between the AV perception and acceptance among non-motorist roadway users.

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