What are the factors determining user intentions to use AV while impaired?

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Abstract

In this study, we employ the Integrated Choice Latent Variable (ICLV) framework to model the public's intention of using Autonomous Vehicles (AVs) while impaired under the influence of alcohol, medicine, or fatigue. We identify five latent constructs from psychometric indicators that define respondent's perception and attitudes towards AVs which are i) perceived benefits, ii) perceived risks, iii) enjoy driving, iv) wheels public transport attitude, and v) rails public transport attitude. We use these latent variables along with explanatory variables to study user intentions regarding delegation of vehicle control from human driving to autonomous driving. The study uses survey data collected from 1,065 Czech residents between 2017 and 2018. Our findings indicate that user intentions are primarily defined by attitudes rather than socio-demographic attributes. However, the inclusion of both types of variables is crucial in evaluating user intentions. Despite a positive outlook towards AVs, people were found to be reluctant in using AVs while impaired which can be attributed to distrust towards the technology. Our analysis shows that with appropriate efforts from policymakers, the public's attitude can be changed to promote adoption. The efforts will have to be emphasized towards building positive attitudes (such as perceived benefits) and diminishing existing negative attitudes (such as perceived risks).

Keywords: latent variables; attitudes; hybrid choice model; AV use

1. Introduction

The idea of Autonomous Vehicles (AVs) has brought rapid technological innovations in travel patterns; a trend that is likely to dominate the automotive sector in the future. AVs capable of operating on their own (i.e., without human intervention) is expected to bring significant benefits to current transportation systems

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and change the way we travel. Removal of the human element in driving is expected to reduce highway crashes and traffic congestion, and provide better access to population groups who cannot drive (Ashraf et al., 2021; Fagnant and Kockelman, 2015; Krechmer et al., 2016; Public Service Consultants and Center for Automotive Research, 2017). The elderly, disabled, children, and individuals who are unable to drive, due to their medications or physical and psychological limitations, constitute the majority of non-driving groups. According to Litman, (2019), these non-driving groups can constitute up to 30% of residents in any community, and removing their dependency on other drivers would greatly increase their mobility (Fagnant and Kockelman, 2015). Besides this, those with a temporary inability to drive, for example, people under the influence of alcohol, medications, or those that are physically or mentally fatigued can elect to ride in AVs for a safer trip. Studies suggest that fatal crashes arising from drunk and fatigued drivers alone account for 29% and 2.5% of all fatal crashes in the US, respectively (Kalra, 2017). These fatalities could be reduced or better eliminated with the use of AVs.

With AVs, drivers will no longer need to be in control of the vehicle or pay attention to the road. This will allows drivers to engage in activities like working, reading, or sleeping like passengers do (Krueger et al., 2016). This can reduce stress on the driver and allow them and the passengers to spend travel time productively reducing overall travel time costs. It is plausible that a driver's intention to maintain control of the car or relinquish it in lieu of engaging in other activities will be based on specific situations at hand. Additionally, their intention might also be affected by their outlook and attitude towards AVs. For example, consider a situation where a driver is drunk with a blood alcohol concentration level above the allowable limit and wants to be driven home safely. With AVs available for transportation, the driver might elect to be driven by an AV to avoid safety hazards and legal issues even though they might have precedence for manual driving over automated driving. We assert that such an intention (here to allow AV to drive) is a decision that is affected by the driver's psychology. In the same example, it is safe to assume that an individual with a strong faith in self-driving cars and their potential will be more likely to choose to be driven home compared to someone who has doubts and fears. Therefore, certain situations or scenarios for AV use could be associated with specific psychological factors and recognizing underlying factors can be crucial to better understanding user intention of using AVs. Identification of such underlying factors is particularly useful in studying the acceptance of new emerging technologies.

This study focuses on identifying and evaluating the effects of various latent constructs on user intentions regarding AV use while impaired. Impairment in this study refers to the temporary loss in sensory and/or cognitive functions due to alcohol, medicine, or physical/mental fatigue. Also, our definition of the intention of use refers to user willingness to delegate vehicle control to Automated Driving System under three scenarios of impairment mentioned earlier. This study models psychological constructs as latent variables along with explanatory variables using a choice modeling framework to address the following questions: *What are the latent constructs and socio-demographic attributes that determine people's intentions to use AVs while impaired? Does engage in preferred activities in lieu of driving have a measurable impact on their intention of use?* The rest of the paper is organized as follows. In the following section, we discuss relevant literature under the literature review section followed by a description of the survey and the collected data under the data section. The methodology section then expands upon the modeling approach followed by results obtained from our analysis. We then present the policy implications of our study followed by a discussion of the results and our conclusion. In the discussion and conclusion section, we discuss the significance of our findings and present potential avenues for future research.

2. Literature review

2.1. Use scenarios and user-preferred activities

Past surveys have found that people prefer to spend their time in AVs observing the scenery or watching the road the most followed by reading and talking to others (Bansal et al., 2016; Cunningham et al., 2018; Schoettle and Sivak, 2014). Surveys show that people are expected to increasingly engage in activity with the increase in the level of automation (Kyriakidis et al., 2015). However, individuals reportedly have mixed preferences towards certain activities like sleeping and resting in AV with people being more accepting towards them when tired versus when impaired (Cunningham et al., 2018). One particular survey has reported that people are highly concerned about sharing the road with drowsy drivers (Piper, 2020).

The same survey found that lack of vehicle control and distrust in other drivers were the main reasons for respondents not willing to sleep in an AV.

2.2. Latent constructs and socio-demographic variables

Studies incorporating latent constructs in assessing the public's attitude towards the adoption of AVs suggest that psychological factors or latent constructs have a significant influence on adoption. Literature suggests that factors related to safety, perceived usefulness, reduced emissions, and improved mobility are predominantly positive influencers of adoption (Acheampong and Cugurullo, 2019; Hegner et al., 2019; Rahman et al., 2019; Xu et al., 2018). On the other hand, factors related to uncertainty and risks such as safety risks and concerns, lack of knowledge, and distrust have been reported as the greatest barriers to adoption (Ashkrof et al., 2019; Haboucha et al., 2017; Hegner et al., 2019; Kaur and Rampersad, 2018; Liu et al., 2019a; Nazari et al., 2018; Zmud et al., 2016). Additionally, latent factors pertaining to people's concerns regarding the environment, and preference of using shared and public transportation have also been found to influence individuals' decision to adopt AVs (Ashkrof et al., 2019; Haboucha et al., 2017; Nazari et al., 2018). Subjective norm which refers to the effect on an individual's decision as a result of decisions made by other influential individuals is another psychological factor that has been found to encourage adoption (Jing et al., 2019; Kettles and Van Belle, 2019; Liu et al., 2019a; Zhang et al., 2019).

The effect of an individual's socio-demographic attributes on adoption has been well documented in the literature. Studies in the general point out that young, educated, and technology-savvy individuals are the most likely adopters (Acheampong and Cugurullo, 2019; Bansal et al., 2016; Haboucha et al., 2017; Shabanpour et al., 2018; Winter et al., 2019) although those belonging to older age groups have also been reported to prefer using vehicles with higher autonomy (Rödel et al., 2014). Females, in general, have been associated with greater concerns, and less risk-taking behavior compared to males and therefore have been found to be less accepting of AVs (Bansal et al., 2016; Hulse et al., 2018; Schoettle and Sivak, 2014; Winter et al., 2019). However contrasting results have also been reported suggesting that males are more likely to avoid risks compared to females (Tsirimpa et al., 2009) and that gender is irrelevant in determining consumer's adoption behavior based on their Willingness To Pay (WTP) for AVs (Liu et al., 2019b). Prior knowledge of self-driving cars and higher income has been reported as significant covariates promoting adoption and consumer WTP respectively (Bansal et al., 2016; Kyriakidis et al., 2015; Lee et al., 2017) although a negative correlation between income and general acceptance has also been observed in prior studies (Nordhoff et al., 2018; Zmud and Sener, 2017).

2.3. AVs for people with disabilities

Enhanced mobility for physically and mentally challenged populations has been cited as a potential benefit associated with AVs (Bradshaw-Martin and Easton, 2014; Chapman, 2012; Halsey, 2017; Harper et al., 2016). Potential benefits seem even more relevant in countries like the USA where millions of citizens are estimated to live with at least one disability (Claypool et al., 2017). Additionally, in countries with densely populated urban centers like in the USA, limited availability of public transportation in large cities present serious challenges to people with disabilities compelling them to rely on others for their transportation needs (Brumbaugh, 2018; Rudinger et al., 2004). Research has shown that mobility-restricted individuals often find it difficult to use personal automobiles and public transit (Bezyak et al., 2017; Casey et al., 2013; Ding, et al., 2018; Mishra et al., 2012; Welch and Mishra, 2013; Mishra et al., 2015). Despite potential mobility benefits, people with disabilities have mixed views regarding AVs which can be largely attributed to their inexperience using the new technology (Bennett et al., 2020, 2019; Hwang et al., 2020; Kassens-Noor et al., 2020).

Although AV acceptance among people with disabilities has been investigated by past studies, study related to intentions to use AV among people with temporary impairment seems to have been largely left unaddressed in the literature except for alcohol-induced impairment. Existing research shows that while AVs have the potential to reduce drink-driving behavior skeptics are still reluctant to use them while drunk or while under the influence of medicine (Booth et al., 2020; Nielsen and Haustein, 2018).

2.4. Study objectives

Existing research on AV acceptance for the physically disabled has been largely focused on investigating their attitudes (Bennett et al., 2020, 2019; Hwang et al., 2020), and their travel behavior and needs (Faber and van Lierop, 2020; Harper et al., 2016). Past studies are predominantly based on travel restrictive disabilities while studies on temporary sensory and cognitive travel restrictive impairment have been left out. Inclusion of temporary impairment in AV-related literature is limited to Payre, Cestac, & Delhomme, (2014), Booth et al., (2020), and Nielsen & Haustein, (2018). While these studies have contributed to the literature on impaired driving and AV use, there are limitations in these studies that require further research. We contribute to the existing literature by addressing gaps in existing research as follows:

i. Payre, Cestac, & Delhomme, (2014) report sampling biases in their data concerning gender, aim at specific subgroups of the population (e.g., active drivers), and exclude technology adoption behavior in their study. In our study, we include the general population older than 15 years as the sampling frame regardless of the respondent's driving status. Also, the chosen sampling procedure within the currently presented study produced a sample reflecting the socio-demographic status of the population like a more proportionate proportion of men and women. Furthermore, our analysis includes the technology adoption behavior of the respondents.

ii. The study by Booth et al., (2020) is focused on the extent of AV use and alcohol consumption without accounting for medicine or fatigue-induced impairments while Nielsen & Haustein, (2018) explore people's expectations regarding potential benefits that can be derived from AV without further analysis on variables affecting expectations or the different levels of expectation. To our knowledge, no prior study has addressed intention of use for various impairments by identifying and incorporating latent constructs and socio-demographic variables as we have done in this study.

iii. Current literature investigating AV acceptance among people with impairment or disabilities is limited to the use of latent variable models (for example refer to Becker & Axhausen, 2017; Bennett et al., 2019, 2020; Hegner et al., 2019).In contrast, our study employs an Integrated Choice Latent Variable (ICLV) modeling approach that incorporates a latent variable model and a discrete choice model to investigate the effect of latent variables on user intentions to use AV while they are impaired. We use latent variables to incorporate individual's subjective attitudes and perceptions and investigate their influence on user intention.

It should be pointed that although the ICLV framework has been used to analyze the influence of latent psychological constructs on choice behavior, past studies have raised questions on its applicability. Mainly, its assumption of one-way causality between attitudes and behavior has faced criticism from researchers (Chorus and Kroesen, 2014; Kroesen and Chorus, 2018). On the contrary, Vij and Walker (2016) have demonstrated the framework's ability to analyze complex behavioral theories and lend structures to unobserved heterogeneity through latent constructs overcoming the limitations imposed by simpler choice models. Considering these distinct advantages and the exacting nature of the ICLV framework, current research aims to contribute to its body of literature on AVs.

In the literature, Sharda et al. (2019) have addressed the issue of one-way through latent segmentation of individuals and the use of simultaneous equations modeling two-way relationships between attitudes and behaviors. They conclude that people's attitude is affected by behavior more so than the other way around. However, a notable point of departure between the study and the current study is people's familiarity with the choice alternatives. More specifically, our study focuses on a technology that is relatively new and inaccessible which provides limited scope for individuals to frame posteriori that influences their behavior.

3. Data

3.1. Survey design

Between November 2017 and January 2018, a survey on perceptions and attitudes related to AVs among the general population was conducted in the Czech Republic. Overall, 59 professional inquirers personally interviewed 1,065 persons older than 15 years via computer-assisted personnel interview. Respondents were selected through a multistage probabilistic sampling procedure, based on the list of address points in the country.

In the first step, there were 74 municipalities randomly sampled throughout the Czech Republic. Each of the sampling points included at least ten primary and 30 replacement households. If there were more sampled households per one sampling point (e.g., panel house), in the second step, the desired number of households were randomly sampled from the list. Finally, within each of the selected households, one person older than 15 years was randomly sampled to participate in the survey. Selected households were informed about the survey through a letter. If it was not possible to contact the primary household, interviewers moved to one of the three randomly selected replacement households. The design of the study, sampling procedure, and questionnaire was piloted on 54 individuals in October 2017 and the pilot study was implemented the same way as described in the preceding paragraphs. No substantial issues were identified during the pilot study.

Fig. 1. Summary of responses for a) key socio-demographic variables, and b) preferred activities while traveling in an AV

The interview itself focused on the respondent's socio-demographic attributes and issues associated with self-driving vehicles along with related topics such as prior knowledge of AV, experience using Advanced Driver Assistance System (ADAS), attitudes towards new technology in general. To achieve comparability of the results, the used methods were adopted from the ongoing research in this area (see Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019; Payre et al., 2014; J. Zmud et al., 2016).

Fig. 1 shows the share of different responses received for explanatory variables used in this study. To understand AV familiarity, respondents were asked "*Have you ever heard about autonomous vehicles before participating in this survey?*" along with "*Yes*", "*No*" and "*I don't know*" as the response alternatives. About 29% of participants heard about autonomous vehicles before the survey. The questionnaire on general attitude and perceptions towards AVs asked the respondents for an answer on standardized Likert scales. The summary of responses for these psychometric indicators is presented in **Fig. 2** along with the name given to the indicators. The indicators in the figure are grouped based on similarity of scale for better readability. The reader is advised to refer to **Table 1** for questions related to the indicators.

3.2. Modeling approach

The survey presented the respondents with various scenarios regarding safety, cost, and legal liability, and collected data on their intention of AV use. The respondents were asked to express their agreement to AV use in different scenarios on a seven-point Likert scale ranging from "I Strongly Disagree" to "I Strongly Agree". More specifically, the questions asked the individuals of their willingness to delegate driving to Autonomous Driving System for different scenarios of impairment which were i) when drunk, ii) when under the influence of medication, and iii) when tired or fatigued. These measures were designed in alignment with the published research. We can see a substantial inclination towards (strongly) agree, the rest of the scale's granularity level is unnecessary detailed (shown in **Fig. 3**). Their distribution was tackled by normalizing them into three categories by summing their *z* scores (see Ward et al., 2008). Similar value distribution was also reported by Payre et al. (2014) from which these measures were derived. To quote the authors, "Interest in using automated driving while impaired: e.g. I would delegate the driving to the automated driving system if: I was over the drink driving limit, M = 6.11, SD = 1.67, min = 1, max = 7; I was tired, M = 5.38, SD = 1.87, min = 1, max = 7; I took medication that affected my ability to drive, M = 5.42, SD = 1.97, min = 1, max = 7." The internal consistency for the combined variables measured using Cronbach's Alpha was of excellent reliability with a value of 0.92 (Hinton et al., 2004). The responses

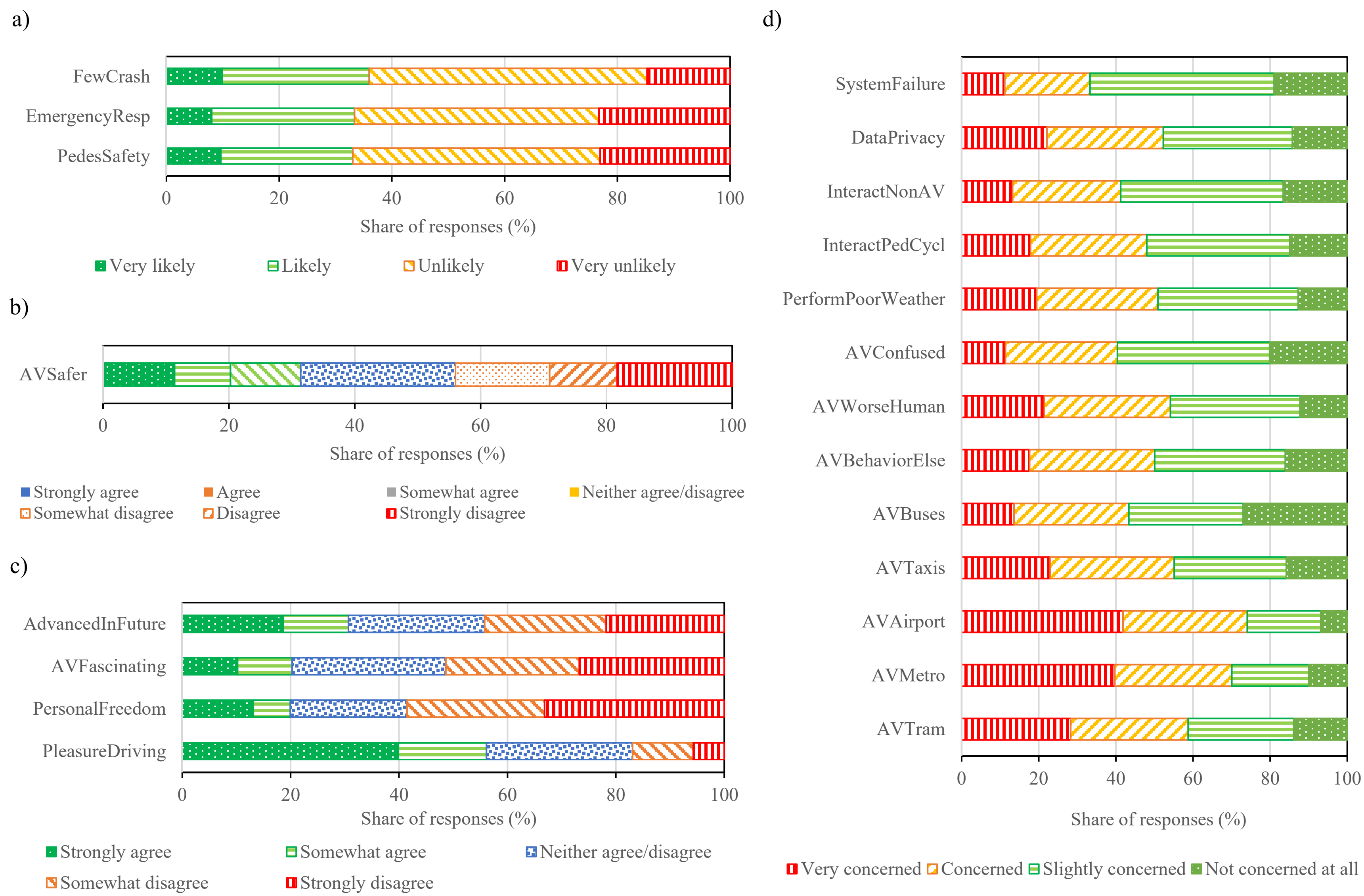

Fig. 2. Summary of responses for indicator variables collected over different Likert scales a), b), and c) for indicators associated with perceived benefits, and d) for indicators associated with worries and concerns.

a)

b)

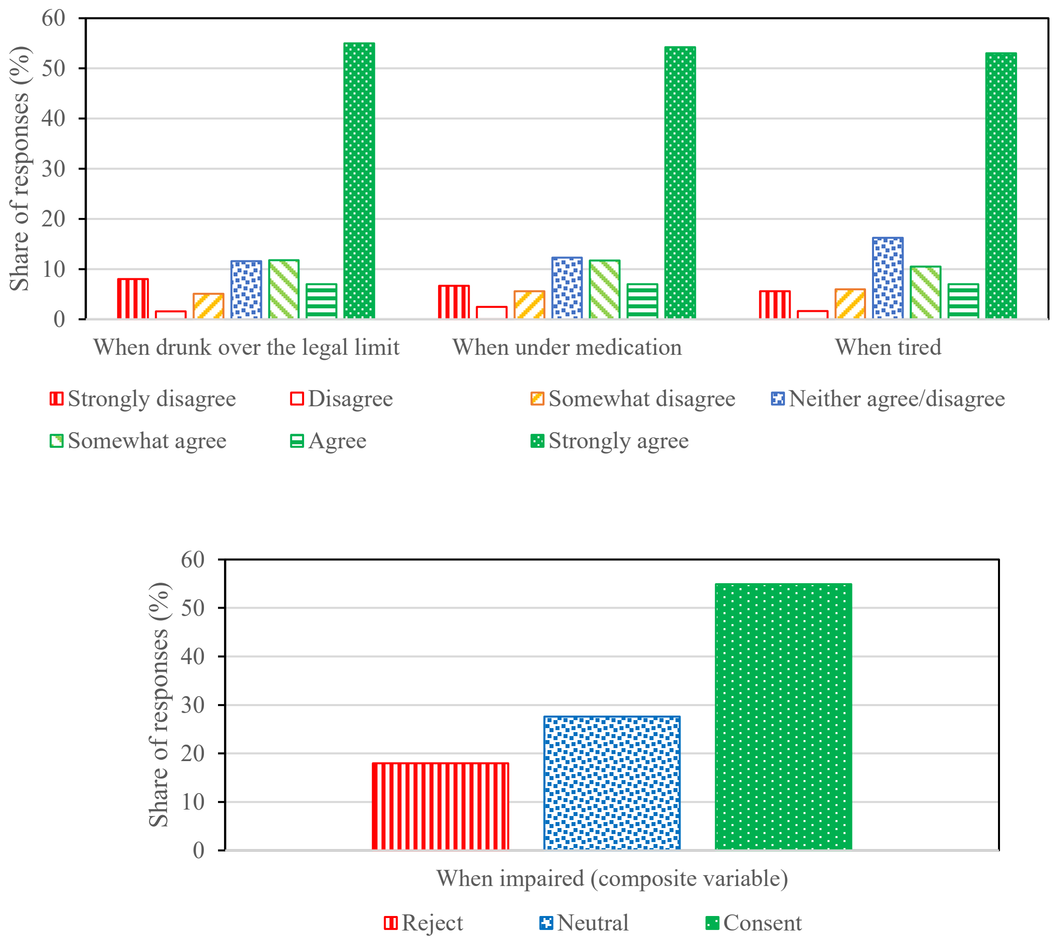

Fig. 3. Summary of responses a) obtained from the survey on three scenarios, and b) for the standardized composite variable.

on the composite variables were then standardized to a 3-point Likert scale. Following the standardization, the responses under categories 1,2,3 formed the first category; responses 4,5 formed the second category; and responses 6,7 formed the third category which we refer to as “Reject”, “Neutral”, and “Consent” respectively. Our model estimation began with the identification of latent variables using Exploratory Factor Analysis (EFA). We then incorporated the identified latent variables and explanatory variables into a choice model using the ICLV framework with an ordered logit kernel (Walker and Ben-Akiva, 2002). Our approach used a simulation technique for estimating model parameters (for a description of estimation of approaches please refer to the following section). All model estimations were carried out in PandasBiogeme v3.2.5 (Bierlaire, 2018).

4. Methodology

Perception and attitudes represent an individual's latent beliefs and values and unlike observable variables cannot be directly measured. These latent constructs however influence an individual's decision-making process (Ben-Akiva et al., 2002). Latent constructs can be identified using psychometric indicators in surveys. Indicators in survey questionnaires can be questions that ask respondents to rate certain attributes on a scale. Our goal was to investigate the public's intention as choice alternatives and gain insights into the user's decision-making process through structural and measurement relationships between variables therefore, we use the ICLV modeling approach (Vij and Walker, 2016). The following sections present an overview of the ICLV framework and estimation techniques used to estimate model parameters for ICLV models.

4.1. ICLV framework

ICLV models consist of three main components: i) structural equations, ii) measurement equations, and iii) choice model. The first two components together form the latent variable model and their integration with a choice model is referred to as the ICLV model. **Fig. 4** presents a schematic of the framework applied to this study. The latent variables are presented within ellipses while observable explanatory variables are represented within rectangles. Straight lines represent the structural equations between the variables and the dashed lines represent the measurement relationships.

4.1.1. Structural equations

Latent variables are characterized by structural equations that link observed explanatory variables with unobserved latent variables. For a (K x 1) vector of explanatory variables x and latent variables x^*, structural equations can be written as

$$x^* = \beta^s * x + \gamma^s \tag{1}$$

where, β^s is a (M x K) coefficient matrix estimated from the data, γ^s represents the random error terms which are assumed to be independent and normally distributed with covariance matrix μ, and x^* is an (M x1) vector of the latent variables. This results in one structural equation for each latent variable. The utility associated with the choices is also a latent construct whose structural equation can be written as

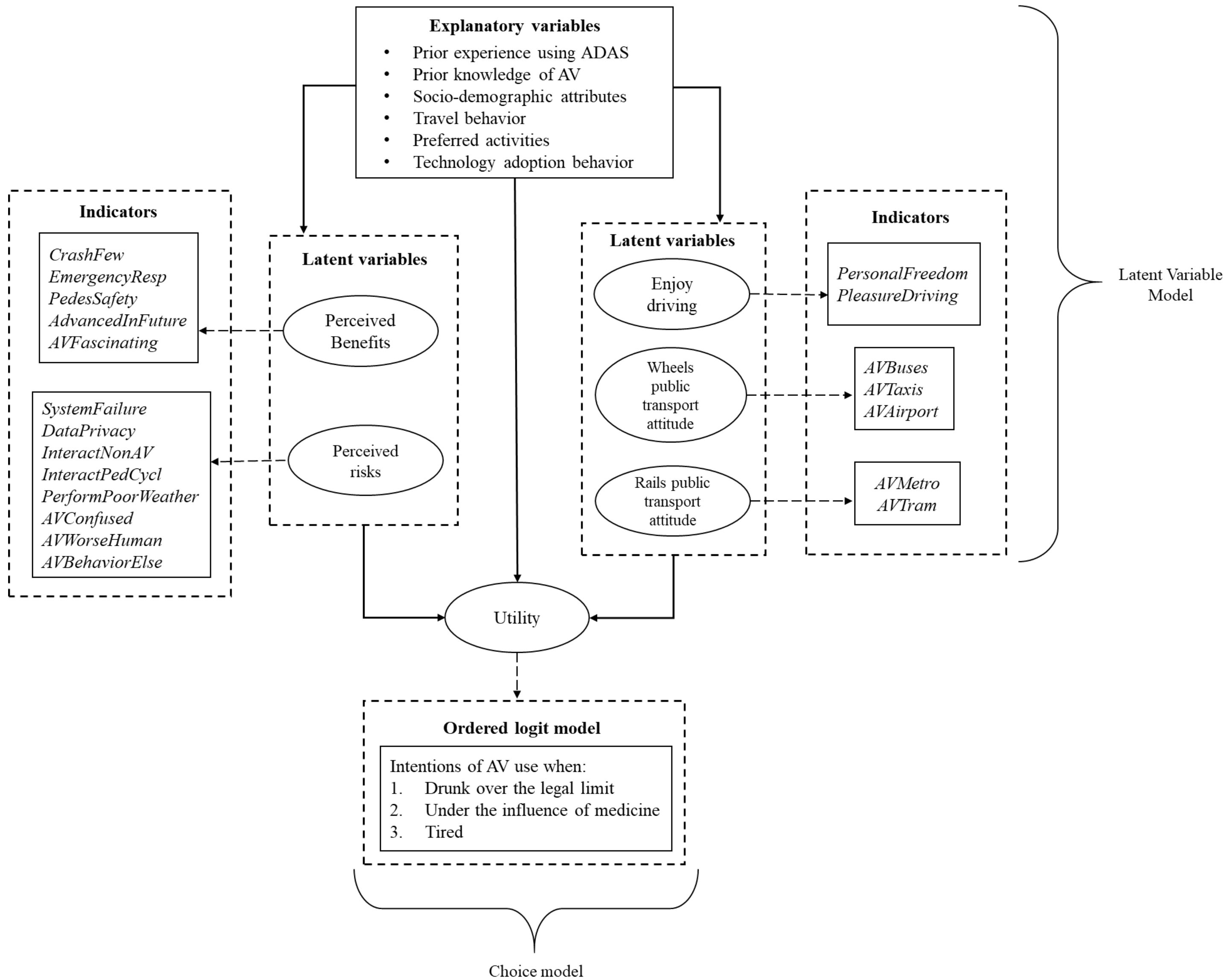

Fig. 4. ICLV framework showing the explanatory variables, latent variables, and associated indicators.

$$U_n = Ax + Bx^* + \gamma^u \tag{2}$$

where, U_n represents the utility for individual *n* obtained using coefficients estimated for (*K* x 1) observed variables *x* and (*M* x 1) latent variables x^* with estimated coefficients *A* (1 *X K*) and *B* (1 x *M*) respectively. The error represented here by γ^u is assumed to be independent and logistically distributed with the covariance matrix σ.

4.1.2. Measurement equations

The latent variables are identified from indirect measurements which are a manifestation of the underlying latent identity. Measurement equations are used to establish relationships between the indicators and the latent variables. The measurement equation for the indicators can be written as

$$z = \beta^m * x^* + \gamma^m \tag{3}$$

where *z* is a *(N* x 1*)* vector of discrete random indicator values, β^m is a (*N* x *M*) coefficient matrix estimated from the data for (*M* x 1) vector of latent variables x^* obtained from Eq. (1). Here, γ^m is the random error terms assumed to be independent and normally distributed with the covariance matrix λ. Then, for a set of indicators *I* taking discrete values $i_1, i_2, \ldots, i_j, \ldots. i_k$ the measurement equation based on ordered probit kernel can be written as

$$I = \begin{cases} i_1 & if\ z < \tau_1 \\ i_2 & if\ \tau_1 \le z < \tau_2 \\ & \vdots \\ i_j & if\ \tau_{j-1} \le z < \tau_j \\ & \vdots \\ i_k & if\ \tau_{k-1} \le z \end{cases} \tag{4}$$

where *z* is a *(N* x 1*)* vector of random variables obtained from the Eq.(3), and $\tau_1, \tau_2 \ldots. \tau_{k-1}$ are threshold parameters that are strictly ordered ($\tau_1 \le \tau_2 \le \cdots. \le \tau_{k-1}$). Then, for three alternatives represented by y_n, the choice representation can be written as:

$$y_n = \begin{cases} 1 & if\ U_n < \theta_1 \\ 2 & if\ \theta_1 \le U_n < \theta_2 \\ 3 & if\ U_n \ge \theta_2 \end{cases} \tag{5}$$

where U_n is the utility function as explained in Eq. (2), and θ_1, θ_2 are estimated threshold coefficients.

4.1.3. Integrated model and estimation

Eqs. (1), **(3),** and **(4)** together represent the latent variable model while **Eqs. (2)** and **(5)** represent the choice model for the integrated model. Parameter estimation for ICLV models is done using maximum likelihood approaches either using sequential estimation or simultaneous estimation. In sequential estimation, the parameters for the latent variable model are estimated first followed by the choice model. This enables the addition of latent variables into the choice model. This approach although computationally less demanding provides inconsistent parameter estimates as it assumes that latent variables are independent of the choice model. In contrast, simultaneous estimation overcomes this limitation by estimating unknown parameters for both models using simultaneous numerical integration to maximize the likelihood function. In this study, we employ simultaneous estimation to estimate parameters for the ICLV model. The likelihood function for the simultaneous equation is a joint probability of variables y_n and z conditional upon x. This is given by **Eq. (6)**:

$$L(y_n|x, x^*; A, B,, \beta^s, \mu, \beta^m,) = \int_{x_v^*} f(y_n|x, x^*; A, B,) f_1(z|x, x^*; \beta^m,) f_2(x^*|x; \beta^s, \mu) dx_v^* \qquad (6)$$

In Eq. (6) the first integrand corresponds to the structural equation of the choice model. The second and third integrands correspond to the measurement equation and structural equation of the latent variable model, respectively. Recall that the density function f here is estimated using the ordinal logit framework (**Eq. (2)**). The joint probability of y_n, z and x^* is integrated over the vector of latent variables x_v^*. Monte Carlo simulation that draws samples from the normal distribution of the latent variables x^* is then used to evaluate the integral. We use Monte Carlo simulation with 150 Halton draws to evaluate the integral (Sharma and Mishra, 2020). The resulting likelihood estimation is therefore called Maximum Simulated Likelihood.

5. Results

5.1. Exploratory Factor Analysis

In our EFA we used varimax rotation and a cutoff of 0.4 for the factor loadings (Guadagnoli and Velicer, 1988; Stevens, 2009). Bartlett's test for sphericity and Kaiser-Meyer-Olkin (KMO) test for sampling adequacy was satisfactory with a p-value less than 0.05 and KMO value 0.86. The construct associated with the first five indicators concerned with the public's perception of benefits were identified as **perceived benefits** since they illustrated potential benefits from the adoption of self-driving vehicles (Acheampong and Cugurullo, 2019; Liu et al., 2019a). The next nine indicators explained respondent's concerns and worries regarding the performance of AVs and their interaction with other road users. We identified the latent variable associated with these indicators as **perceived risks** (Choi and Ji, 2015; Liu et al., 2019a). The next two indicators expressed the respondent's experience while driving a conventional car hence the corresponding latent variable for the indicators was named **enjoy driving** (Haboucha et al., 2017). The remaining indicators explained the public's worries regarding autonomous transit systems. To better distinguish between the latent variables we differentiated them based on wheels (buses and taxis) and rails (subway metro and electric surface trams) and referred to them as **wheels public transport attitude** and **rails public transport attitude** respectively (Haboucha et al., 2017). **Table 1** presents the results from the factors analysis along with values for standardized Cronbach's Alpha next to the latent variables. The values for Cronbach's Alpha are indicative of at least moderate reliability among the indicator variables with the lowest value being 0.53 (Hinton et al., 2004). The source of the questionnaire items for the indicators is also presented in the table.

5.2. Latent variable model: structural and measurement equation models

The results from the structural and measurement equations model are presented in **Table 2** and **Table 3** respectively. The table is outlined as follows. The first column in the tables presents the variables and indicator variables for the measurement models and structural equation models respectively followed by the estimated coefficients for the latent variables and robust t-statistics for the estimates.

The structural equation models establish relationships between the latent variables and the explanatory variables. A positive sign on the estimate for **heard of self-driving cars before** for perceived benefits and

Table 1

Factor loadings on the indicators.

Latent variable	Indicators	Source	Loading
Perceived benefits **(α=0.72)**	*FewCrash*: I believe self-driving cars will reduce crashes[#]	Schoettle and Sivak (2014)	0.71
	EmergencyResp: I believe self-driving cars will improve emergency response[#]	Schoettle and Sivak (2014)	0.56
	PedesSafety: I believe self-driving cars will improve pedestrian safety[#]	Schoettle and Sivak (2014)	0.58
	AdvancedInFuture: I believe advanced self-driving cars will make human driving irresponsible in the future *	Nielsen and Haustein (2018)	0.42
	AVFascinating: I think self-driving cars are a fascinating idea *	Nielsen and Haustein (2018)	0.41
	AVSafer: I believe self-driving cars will provide me with greater safety **	Payre et al. (2014)	0.41
Perceived risks **(α=0.85)**	*SystemFailure*: I am worried about system failure in self-driving vehicles***	Schoettle and Sivak (2014)	0.56
	DataPrivacy: I am worried about data privacy in self-driving cars***	Schoettle and Sivak (2014)	0.54
	InteractNonAV: I am worried about self-driving cars interacting with other human-driven vehicles***	Schoettle and Sivak (2014)	0.56
	InteractPedCycl: I am worried about self-driving cars interacting with pedestrians and cyclists***	Schoettle and Sivak (2014)	0.61
	PerformPoorWeather: I am worried about the performance of self-driving cars in poor weather***	Schoettle and Sivak (2014)	0.66
	AVConfused: I am worried about self-driving cars being confused in complex situations***	Schoettle and Sivak (2014)	0.73
	AVWorseHuman: I am worried that self-driving cars will drive worse than human-driven cars***	Schoettle and Sivak (2014)	0.68
	AVBehaviorElse: I am worried about self-driving cars behaving in an unexpected manner***	Schoettle and Sivak (2014)	0.56
Enjoy driving **(α=0.53)**	*PersonalFreedom*: I feel personal freedom driving a vehicle***	Haboucha et al. (2017)	0.86
	PleasureDriving: I feel pleasure driving a vehicle***	Haboucha et al. (2017)	0.72
Wheels public transport attitude **(α=0.72)**	*AVBuses*: I am concerned about self-driving buses***	Schoettle and Sivak (2014)	0.77
	AVTaxis: I am concerned about self-driving taxis***	Schoettle and Sivak (2014)	0.86
	AVAirport: I am concerned about self-driving vehicles in public areas such as airports***	Schoettle and Sivak (2014)	0.59
Rails public transport attitude **(α=0.86)**	*AVMetro*: I am concerned about self-driving trains/metro***	Schoettle and Sivak (2014)	0.83
	AVTram: I am concerned about self-driving trams***	Schoettle and Sivak (2014)	0.77

[#] Responses collected on a 4-point Likert scale from 1-very likely to 4-very unlikely.

* Responses collected on a 5-point Likert scale from 1-strongly agree to 5-strongly disagree.

** Responses collected on a 7-point Likert scale from 1-strongly agree to 7-strongly disagree.

*** Responses collected on a 4-point Likert scale from 1-very concerned to 4-not concerned at all.

perceived risks suggest that people who have prior knowledge of AVs associate both benefits and risks with self-driving cars although the magnitude of perceived risks is comparatively higher. The positive influence of prior knowledge on people’s attitude is well documented in previous studies (Schoettle and Sivak, 2014; Silberg et al., 2013), however, its effect on perceived risks has not been documented before to the knowledge of the authors. The mixed effect of prior knowledge on the perception of benefits and risks can be attributed to the absence of real work interaction between the public and AV technologies. Although people have a positive outlook towards AVs based on their current knowledge, they might still be undecided about its potential risks and therefore present a mixed outlook of benefits and risks. The variable **enjoy driving** is negatively associated with prior knowledge of AVs. It could be that those with prior knowledge of self-driving cars are predominantly car lovers who are concerned about not being able to drive themselves. As a previous study suggests, those who enjoy driving are less likely to use AV (Silberg et al., 2013). Among activities **texting** and **using the internet** are positively related to the perception of benefits, while **sleeping** is associated with the perception of risk. While being able to communicate with others when traveling is a potential benefit, sleeping might be a concern for users as it involves entrusting personal safety to the driver. This is particularly relevant for public transportation on wheels (buses and taxis). People’s distrust of other drivers while sleeping has been reported by a past survey (Piper, 2020). Surprisingly, respondents that enjoy driving are more likely to sleep while traveling. Although counter-intuitive, it could be that those who enjoy driving are more likely to drive long-haul distances and prefer to rest or sleep in the vehicle. Results from Piper (2020) are indicative of this where about 41% of respondents expressed willingness to sleep in an AV on a long-haul trip. The idea of public distrust towards other drivers is further supported by the positive **sleeping** coefficient for public transportation on rails (metro and tram) in this study. Understandably, people are likely to feel safer falling asleep on a rail-based transportation service versus a wheel-based transportation service. In public rail transportation, in addition to sleeping, people are also likely to engage in using the internet and refrain from **playing games**. In the case of technology adopters, l**aggards** are associated with perception of both benefits and risks although the magnitude of the latter is higher. Among males and females, **females** are found to be more concerned towards public wheels

Table 2
Results from the latent variable model: Structural equation models.

Variables	Perceived benefits		Perceived risks		Enjoy driving		Wheels public transport attitude		Rails public transport attitude	
Structural equations	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**
Constants	-1.97	-1.98	***	***	***	***	***	***	***	***
Heard of self-driving cars before (1=Yes, 0=No or I do not know)	1.31	2.13	3.99	2.88	-8.35	-1.91	-9.02	-2.11	4.68	1.93
Prior ADAS use (1=Yes, 0=No)	-	-	-	-	-	-	-	-	-3.76	-2.95
Activities while traveling in AV (1=Yes, 0=No)										
Text or talk	1.11	2.21	-	-	-	-	-	-	-	-
Read	-		-	-	-	-	-6.97	-2.41	-	-
Use internet	1.24	2.52	-	-	-	-	-12.31	-1.98	5.21	1.97
Play games	-	-	-	-	-	-	17.41	1.87	-4.81	-2.21
Sleep	-	-	1.69	1.54	17.91	2.47	-21.29	-2.68	5.22	2.59
Watch the road	-	-	-	-	-	-	-9.45	-1.52	4.89	1.89
Work	-	-	-	-	-	-	-	-	-5.19	-1.74
Technology adoption behavior										
Early adopter	-	-	-	-	-	-	-	-	-	-
Late adopter	-	-	-	-	-	-	-	-	-	-
Laggard	1.29	1.92	2.31	1.99	-8.38	-1.86	-13.11	-1.67	3.51	1.89
Gender (1=Female, 0=Male)	-	-	-	-	-	-	-10.41	-2.49	-	-
Highest education level achieved										
Primary or vocational	-	-	1.92	1.85	-	-	-	-	-	-
High school	-	-	-	-	-	-	-	-	-	-
College	-	-	-	-	-	-	-	-	-	-
Frequency of driving previous week										
Not at all	-	-	1.19	2.39	-	-	-	-	-	-
At least once	-	-	-	-	5.62	2.13	-	-	-	-
Everyday	-	-	-	-	-	-	-	-	-	-

***Note: During initial model estimation the magnitude of constants and their t-statistics for latent variables other than perceived benefits were found to be small. The model was estimated after fixing them to zero.

Table 3

Results from the latent variable model: Measurement equation models.

Indicators	**Constant**		**Perceived benefits**		**Perceived risks**		**Enjoy driving**		**Wheels public transport attitude**		**Rails public transport attitude**	
	Coef.	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**	**Coef.**	**Robust t-stat**
Measurement equations												
FewCrash (Base)	-	-	-	-								
EmergencyResp	0.42	4.64	-0.06	-2.69								
PedesSafety	0.37	3.73	-0.12	-3.62								
AdvancedInFuture	0.39	1.93	-0.33	-10.61								
AVFascinating	0.95	1.32	-0.28	-7.59								
AVSafer	0.46	7.67	-0.27	-2.55								
SystemFailure(Base)	-	-			-	-						
DataPrivacy	-0.48	-2.01			0.03	1.84						
InteractNonAV	0.03	1.18			0.04	1.98						
InteractPedCycl	-0.82	-3.77			0.07	1.65						
PerformPoorWeather	-0.53	-2.21			0.05	1.87						
AVConfused	-0.24	-1.95			0.06	2.01						
AVWorseHuman	-0.61	-2.31			0.05	1.95						
AVBehaviorElse	-0.41	-1.39			-0.01	-2.01						
PersonalFreedom (Base)	-	-					-	-				
PleasureDriving	-0.35	-0.69					-0.03	-5.21				
AVBuses (Base)	-	-							-	-		
AVTaxis	-0.77	-0.95							-0.02	-3.13		
AVAirport	-1.42	-1.67							-0.01	-0.96		
AVMetro (Base)	-	-									-	-
AVTram	-0.23	-0.12									0.04	12.81

transportation than males. This finding is in agreement with past findings suggesting that females show greater concerns than males (Hulse et al., 2018; Winter et al., 2019). Those with **primary or vocational education** seem to be less concerned about risks. Those who **drove at least once the previous week** seemed to **enjoy driving** suggesting that habitual drivers are more likely to like driving. From the results, it is observed that coefficients of the explanatory variables in the structural equation for the latent variables enjoy driving and wheels public transport attitude is high compared to others. This could be explained by people's familiarity with driving and using wheel-based public transport.

The measurement equation models represent the relationship between the latent variables and associated indicators. Here, the measurement equations are estimated by fixing the intercept and an indicator variable at zero. The corresponding indicator variable is referred to in the table as the base relative to which the remaining measurement equations are estimated. For example, for **perceived benefits**, loadings for associated indicators are negative indicating that those with a strong belief in AV benefits strongly agree to their safety benefits and future advancement. Note that most of the perceived benefits are largely associated with safety and future advancement in AV. It is plausible that people strongly believe that AVs in the future will be advanced enough to be safer than human drivers making manual driving irresponsible. Similarly, the loadings on indicators for **perceived risks** imply that concerns regarding system failure and AV behaving unexpectedly (*AVBehaviorElse*) are more important to the user. People are less concerned with data privacy; the performance of AVs; and their interaction with conventional vehicles, pedestrians, and cyclists compared to AVs operating unexpectedly. Since the potential consequences of system failure and AVs behaving unexpectedly could have serious implications to the safety of the driver and road users, people might associate greater risks with these compared to less dire concerns such as data privacy and performance. The negative loadings on **enjoy driving** suggests that users who enjoy driving are concerned about deriving pleasure from driving conventional cars. Loadings for **wheels public transport attitude** and **trains public transport attitude** are suggestive of public's concern regarding autonomous taxis and buses operating in public areas, and their indifference towards autonomous trains and trams, respectively. Since self-driving cars and buses will have to share the road with other road users and will be able to travel without restrictions, this might be a concern for those who frequently use public wheel transportation or travel on the road. On the contrary, those who use transit rails might be less concerned since rails are restricted to their tracks and unlike vehicles on the road, they do not share their tracks with other vehicles or users.

5.3. Ordered logit model

Table 4 presents the results from the ICLV model. The table presents the variable coefficients and t-statistic associated with them along with goodness of fit measures. The ICLV model is found to fit the data well based on Chi-square test statistic derived from the log-likelihood ratio test, i.e., $\chi^2 = 8{,}140.05$ at p-value < 0.005. Note that we provide behavioral interpretation of the results for variables with |robust t-statistics|>1.28 or values statistically significant at a 20% level of significance. The estimated coefficients in the model can be interpreted using their respective coefficients. Positive and negative coefficients for the variables represent higher propensity towards "*consent*" and "*reject*" respectively. The latent variables, **perceived benefits,** and **perceived risks** show a higher propensity towards rejection of AV use while impaired implying that despite an increase in perceived benefits, people are still likely to reject using AV while impaired. The contradicting results could be a result of control associated with the prospective situation (Golbabaei et al., 2020). When users are presented with limited choices for commute risk perception associated with the mode of transportation could affect their perception of benefits. On the other hand, as expected perceived risk is associated with lower acceptance meaning with the increase in perceived risks, people are likely to reject using an AV. Past study has shown similar findings concerning the relationship between perceived risks and AV acceptance based on consumer WTP (Liu et al., 2019a). These results are indicative of people's reluctance to use AV despite having a positive perception of it. Finding from a previous study also suggests that AV skeptics are unwilling to drive in AVs while impaired (Nielsen and Haustein, 2018). This can be attributed to public distrust towards AVs. Trust has been observed to be a strong influencer of behavioral intention to adopt AV (Choi and Ji, 2015) and distrust could be a reason for the public's reluctance. Therefore, it is likely that those who have a positive outlook towards the potential benefits from AV will nonetheless prefer not to use it while impaired. The opposite signs for the latent variables for wheels and rail public transport attitude are noteworthy. This could be explained by modal familiarity. Research has shown that people are more accepting of the transport mode they are more familiar with (Cain et al., 2009). Additionally, this could also be explained by people's cultural inclinations. For example, it was found that subway systems in Stockholm were associated with more negative characteristics compared to other public transport. This was attributed to noise and user's preference to be in daylight (Scherer and Dziekan, 2012).

Table 4

Results from ordered logit model.

Variables	**Coef.**	**Robust t-stat**
Constant	-0.89	-4.61
Prior ADAS use (1=Yes, 0=No)	0.61*	2.48
Activity while traveling in AV (1=Yes, 0=No)		
Read	0.73*	3.04
Mode of travel to work/school		
Car	-0.39*	-1.98
Latent variables		
Perceived benefits	-0.16*	-4.47
Perceived risks	-0.03*	-2.21
Enjoy driving	0.05#	1.89
Wheels public transport attitude	0.004*	1.98
Rails public transport attitude	-0.03#	-1.61
Thresholds		
Threshold 1	-0.09	-1.03
Threshold 2	1.54	2.63
Model goodness of fit		
Rho-square	0.137	
Adjusted Rho-square	0.133	
Initial log-likelihood	-29,706.99	
Final log-likelihood	-25,636.25	
Log-likelihood ratio	8,140.05	
AIC	51,517.92	
BIC	52,106.89	

Level of significance: #p<0.1, *p<0.05

Prior ADAS users are more likely to show positive intentions towards using AV. This finding is in agreement with past studies (Bansal et al., 2016; Kyriakidis et al., 2015). It could be that a positive experience with AV-related technologies entrusts confidence in the user. It is worth mentioning here that no visible relationship between prior knowledge of AVs and intention is evident from the model. This finding however could be attributed to the relatively lower share of respondents (28.7%) having prior knowledge of AVs. For user-preferred activities **reading** is found to be associated with a higher propensity of acceptance and those who **drive to work, or school** displayed less propensity towards acceptance. For those who drive to work or school, cars might be associated with everyday commute therefore these individuals may choose to reject using cars when impaired. Similar results on preferred activities have been reported by Schoettle & Sivak, (2014) who found reading to be the second most preferred activity among survey respondents in the USA and the UK although not in the context of impaired driving. Based on the result and past studies, it can be inferred that people are likely to retain their preference on activities regardless of being impaired or not.

Most of the socio-demographic variables investigated in the study were not found to influence user intentions. This finding is partially supported by previous research that reports the insignificant role of socio-demographic covariates in AV acceptance (for example, age (Payre et al., 2014; Zmud et al., 2016), income (Schoettle and Sivak, 2014), and education (Zmud et al., 2016)). Similarly, driving frequency was also found to be insignificant supporting a previous find (Rödel et al., 2014). The latent constructs-**enjoy driving** and **rails public transport attitude** has a positive and negative effect on intention respectively. The role of **enjoy driving** on the intention of use found here differs from that in the literature which reports a negative relationship between the two (Silberg et al., 2013). This implies that people would likely enjoy riding on an AV while impaired. This could be associated with people's willingness to derive pleasure from other activities when they are unable to drive themselves. Those who are less concerned with riding on public rail transport are less likely to use AV while impaired. This could be due to their greater concern towards wheel-based public transport versus rail-based public transport. The model results in general are suggestive of the importance of including attitude and explanatory covariates in evaluating user intentions to use AVs.

5.4 Mediation analysis

Two explanatory variables namely **prior ADAS use** and **read** as an activity while traveling are present in the final choice model as well as structural equation models. Therefore, mediation analysis was conducted to ascertain the effect of latent variables on the intention of AV use. We follow the generally adopted practice to representing the variables in mediation analysis, i.e., X=explanatory or independent variable, M=mediator or latent variable, and Y=response or the dependent variable (Baron and Kenny, 1986). To test for the effect of latent variables regression between explanatory, latent, and outcome variables was carried out (Baron and Kenny, 1986) followed by a test for statistical significance of mediation effects using non-parametric bootstrapping (Tingley et al., 2014).

Results from the regression equations for mediators of both explanatory variables are shown in **Table 5**. The first column presents predictor variables in the regression. The remaining columns present the

Table 5

Results from regression for mediation analysis.

Predictor variables	**Response variables (Path)**			
Prior ADAS use (X)→Rails public transport attitude (M)→Intention to use AV (Y)				
	Rails public transport attitude (X→M)		**Intention to use AV (X+M→Y)**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**
Constants	0.13	10.71	0.03	1.23
Prior ADAS use (1=Yes, 0=No)	-0.28	-11.59	0.26	1.73
Rails public transport attitude			-1.21	-4.13
Thresholds				
Threshold 1			-1.43	-16.52
Threshold 2			-0.24	-2.01
Model goodness of fit				
Adjusted R-squared	0.172			
McFadden adjusted R-squared			0.011	
Read (X)→Wheels public transport attitude (M)→Intention to use AV (Y)				
	Wheels public transport attitude (X→M)		**Intention to use AV (X+M→Y)**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**
Constants	-1.58	-15.63	0.07	1.88
Activity while traveling in AV (1=Yes, 0=No)				
Read	0.44	2.88	0.59	4.23
Wheels public transport attitude			-0.01	-0.11
Thresholds				
Threshold 1			-1.38	-9.86
Threshold 2			0.14	1.37
Model goodness of fit				
Adjusted R-squared	0.016			
McFadden adjusted R-squared			0.013	

coefficients obtained from regression for different response variables along with their t-stat. Results from two regression are presented, first between X and M, and the second between X, M, and Y.

Table 6

Results from mediation analysis.

Average effects	**Response**			
	Reject	**Neutral**	**Consent**	**p-value**
Prior ADAS use → Rails public transport attitude→Intention to use AV				
Prior ADAS use (1=Yes, 0=No)				
Indirect effects				
Yes	-0.026	-0.027	0.053	0.000
	[-0.042, -0.011]	[-0.038, -0.015]	[0.025, 0.081]	
No	-0.033	-0.023	0.057	0.000
	[-0.046, -0.0176]	[-0.035, -0.010]	[0.029, 0.082]	
Direct effects				
Yes	-0.031	-0.031	0.063	0.090
	[-0.072, 0.006]	[-0.069, 0.005]	[-0.011, 0.139]	
No	-0.038	-0.028	0.065	0.090
	[-0.079, 0.008]	[-0.064, 0.004]	[-0.012, 0.143]	
Total effects	-0.064	-0.055	0.120	0.001
	[-0.102, -0.029]	[-0.091, -0.022]	[0.053, 0.191]	
Read →Wheels public transport attitude→Intention to use AV				
Activity while traveling in AV (1=Yes, 0=No)				
Read				
Indirect effects				
Yes	0.00011	0.00009	-0.0002	0.955
	[-0.003, 0.005]	[-0.003, 0.004]	[-0.008, 0.007]	
No	0.00015	0.00006	-0.0002	0.955
	[-0.005, 0.007]	[-0.002, 0.002]	[-0.008, 0.007]	
Direct effects				
Yes	-0.087	-0.058	0.143	0.000
	[-0.125, -0.049]	[-0.086, -0.032]	[0.082, 0.203]	
No	-0.086	-0.057	0.142	0.000
	[-0.124, -0.049]	[-0.086, -0.032]	[0.082, 0.203]	
Total effects	-0.086	-0.057	0.142	0.000
	[-0.122, -0.050]	[-0.085, -0.031]	[0.082, 0.202]	

For path X→M, both the explanatory variables have a statistically significant relationship with their respective latent variables indicating. In mapping the relationships between X+M→Y for **Prior ADAS use** and latent variable **rails public transport attitude** partial mediation is observed since the effect of the explanatory variable does not disappear with the addition of the latent variable. However, the influence of the explanatory variable *Read* on the response variable does not diminish or disappear with the addition of the latent variable **wheels public transport attitude** suggesting an absence of mediation effect.

Results from non-parametric bootstrapping tests for statistical significance of mediation are presented in **Table 6**. The explanatory variables are presented in the first column. Its effect on the response variable (direct, indirect, and total) are stratified by the three levels in the response variable and presented along with a 95% confidence interval. The total affects here is the effect of X on Y without M; the direct effect is the effect of X and M on Y, and the indirect effect is the difference between total and direct effects. The last column in the table presents the p-value for the statistical significance of the effects. A negative value of an explanatory variable on a certain level of the response variable is indicative of its negative effect on the response. Similar to the findings from regression, indirect and indirect effects are statistically significant for the latent variable **rails public transport attitude** with p-values<0.01 and p-value<0.05 respectively. Only the direct effect of **wheels public transport attitude** is statistically significant (p-value<0.01) indicating only direct effect with no mediation.

6. Policy implications

We present the potential implications of this study based on the marginal effects of the variables in **Table 7**. Among the significant variables (observed and latent) attitude towards wheels-based public transport shows the highest marginal effects. Increase in wheels public transport attitude, the propensity to consent to use of AV (while they are impaired to drive) decreases. That is, with a unit decrease in wheel public transport attitude, about 14% decrease in the probability of the intention of rejection and about 7 % increase in the probability of consent to AV use is observed. Similarly, where there is a unit increase in an individual's perception of risks the probability of rejection increases by about 8% implying that as people's worries regarding the performance of self-driving cars decrease, they are more likely to consent. The marginal effects for perceived benefits also show that with the increase in perception of benefits, people are gradually more likely to consent to use AVs. Comparable results are observed for the public's experience using ADAS technologies and for those who use a car to travel to work or school.

Table 7

Estimated marginal effects for significant variables in the ICLV model.

Explanatory variables	**Reject**	**Neutral**	**Consent**
Prior ADAS use (1=Yes, 0=No)	-0.0023	-0.0009	0.0011
Activity while traveling in a self-driving vehicle (1=Yes, 0=No)			
Read	0.00170	0.0026	-0.0019
Mode of transportation to work/school			
Car	-0.0114	-0.0021	0.0031
Latent variables			
Perceived benefits	-0.0620	-0.0438	0.0397
Perceived risks	0.0859	0.0338	-0.0401
Wheels public transport attitude	0.141	0.0650	-0.0732

People's attitudes and behavior can be largely shaped by policies. More specifically framing policies that can overrule existing negative attitudes and corroborate positive perceptions and attitudes can be a positive step towards framing a public mindset that is more open to the adoption of self-driving cars (Nazari et al., 2018). Based on the findings from this study, we suggest that policymakers should first look for ways to bolster the public's perception of benefits to an extent where people endow more trust towards AVs than human drivers. This could be achieved by running informative shows on media highlighting AV's potential to provide greater safety and mobility compared to conventional vehicles. Additionally, these informative campaigns should focus on providing firsthand experience to establish and encourage positive behavior (Sharda et al., 2019). Second, the public's perception of risks that primarily stem from concerns regarding the interaction between humans and AVs can be negated by taking steps that familiarize them with the technology. Dissemination of results from influential research through informative advertising campaigns can be helpful in this regard. With increased familiarity and adoption among peers, more people and organizations will likely adopt AVs, gradually diminishing public worries over time (Simpson et al., 2019; Simpson and Mishra, 2020; Talebian and Mishra, 2018; Pani et al., 2020). Therefore, third policymakers and engineers should push towards making AVs accessible to the public. A similar idea is supported by existing research by Bansal et al., (2016) and Jing et al., (2019). We suggest that in the initial stages of adoption, AV cars be made available to the public for shared use in short commutes so that a positive attitude in the public can be progressively installed. This can be achieved by expanding the use of self-driving taxis and buses in public areas beginning at a small scale to allow the public to get acquainted first before large-scale deployment. Fourth, we suggest design engineers and policymakers develop technologies that make self-driving cars more user-friendly by facilitating activities that people most prefer to engage in. For example, following the findings in this study, services that facilitate reading activity could be useful in encouraging people to ride in an AV regardless of them being impaired or not. To facilitate reading activity, for example, transit and shared AVs with safe comfortable seats that enable users to lay down and engage in reading books or newspapers can help install a positive attitude in the public. Finally, we recommend policymakers keep themselves updated with current AV-related attitudes and concerns among the public as it is likely to evolve with their experiences and exposure to new information.

7. Discussion and Conclusion

In the future, with the introduction and expansion of vehicle autonomy, AVs will have the potential to serve individual users fulfilling their travel demand needs without having them rely on others to drive them. This will particularly facilitate those who are dependent on others such as those without a driving license, young, elderly, or those who are bound by mental/physical limitations that are preventing them from driving. Users might even have the option to decide under what situations and circumstances would they want to be driven by an AV. Understanding the psychological factors and attitudes involved in the public's decision-making process regarding the use of AVs under different situations can be critical to understanding possible AV use-cases at an early stage which could have big implications on their future adoption.

While various studies have investigated the relationship between AV and people with disabilities (Bennett et al., 2020, 2019; Chi et al., 2013; Harper et al., 2016), our study is centered on individuals who might be temporarily impaired due to alcohol, medicine or fatigue. In addressing limitations in previous studies on impaired driving by Payre et al. (2014), Booth et al. (2020), and Nielsen and Haustein, (2018) we uncovered psychological constructs that influence the intention of use. We also investigated the relationship of key explanatory variables on user intentions.

We identified five latent constructs to investigate user intentions to use AV while impaired. These were **perceived benefits, perceived risks, enjoy driving, wheels public transport attitude, and rails public**

transport attitude. Our results show that contrary to past studies **perceived benefits** have a negative influence on user intentions suggestive of people's reluctance towards using AVs while impaired which can be attributed to public distrust towards AVs due to the absence of real-world interaction between them and AV technology. Similarly, **perceived risk** is also associated negatively with user intention as expected (see Liu et al., 2019a). Latent constructs representing respondent's interest in driving conventional vehicles were found to have no significant relationship with user intentions. The same was observed for the **public attitude related to rail transportation**. Public attitude towards **wheel-based public transportation** was found to be positively associated with user intentions.

Among explanatory variables, **prior use of ADAS** and user preference in engaging in **reading** activity while traveling in AV were related to positive intention. It is safe to assume that those with prior experience using AV-related technologies would be more comfortable allowing AVs to drive them while they are impaired. The structural equations also revealed that user's activity preferences varied across different modes of public transportation (wheels and rails). Those who **drove to work or office in their car** were less likely to show positive intention towards AV use which could be a result of habitual driving. Other variables related to respondent's socio-demographic attributes including their technology adoption behavior were found to be insignificant which is suggestive of the findings from Bennett et al. (2020) which reported no meaningful relationship between demographic attributes and willingness to accept AV among people with disabilities (blind people).

Our results from marginal effects identify potential steps that policymakers can undertake to ensure faster adoption of AVs. Policymakers should prioritize enforcing policies that increase positive perceptions and diminish public worries and concerns to address the public's risk perception. Influential ad campaigns and dissemination of information can be simple yet effective means to achieve this. Furthermore, we suggest the public must be introduced to AVs to build their confidence in the technology. This however should be done with caution by limiting initial interaction and gradually introducing AVs so that public reliance and trust towards them grows gradually.

There are several potential avenues for future studies. First, studies can focus on factors defining user intention of retracting control of the vehicle back to themselves. Second, studies can focus on investigating the difference in intentions across different age groups to identify scenarios that are likely to have a common outcome (user intention). Future studies can also evaluate the difference in preference for individuals who use different modes of travel such as private versus shared transportation. Since a previous study has found a significant relationship between latent effects and behavior with intention as a mediator (see Thorhauge et al. (2019)), the same can be explored to investigate user acceptance with intentions of use as a potential mediator.

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