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Data Issues and the Road Ahead: Multivariate Modeling of Public Interest in Connected Vehicle Adoption

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Abstract

Connected vehicles (CVs) present a wide range of potential benefits, including the distribution of reliable and critical information to motorists and providing valuable big data to transportation professionals. With all the prospective benefits, the challenge is to bring CVs to the real world via widespread adoption. Regardless of the timeline of deployment, prior understanding of the possible barriers to the adoption and usage of CVs will help stakeholders improve public attitude and intention towards adoption. This study splits CV adoption into three distinct but related forms: intentions to ride, own, and recommend CVs, and uses a multivariate ordered probit model to assess the impact of individual characteristics and latent variables—perceived data privacy, perceived data security, and importance of reputation of data manager—on these three forms of CV adoption. While all three latent variables have a positive impact on all forms of adoption, they have the greatest impact on intention to ride compared to intentions to own and recommend. Based on the findings, this study recommends stakeholders to increase transparency and strength of data privacy and security practices as well as to focus educating and marketing on certain population segments to increase CV adoption.

Keywords: Connected vehicles; Adoption interest; Data issues; Data privacy; Data security

1. Introduction

With growing negative externalities of the existing transportation system (Parry et al., 2007), especially with increased safety threats, the disparity in equity and accessibility, and increased environmental impacts, the transportation industry is motivated toward the innovation and development of intelligent vehicle technologies (Guo et al., 2020). These include, but are not limited to, connected vehicles (CVs) having communication abilities, autonomous vehicles (AVs) having self-driving capabilities, and electric vehicles that run fully utilizing renewable electric power. These three vehicle technologies are sometimes conceptualized together, and the combined technology is considered the future of transportation (Toglaw et al., 2018). When AVs, which do not require driving efforts and are accessible and equitable to all groups of population (e.g., older aged, people with disabilities, women, etc.), are supplied with communication abilities and designed to run on electric power, they can make reliable decisions that improve traffic safety (Shetty et al., 2021) and contribute to reducing the environmental impacts of transportation (Pan et al., 2021), respectively. Being a key component of the future of transportation, the focus of this study is the CV technology (CVT).

CVs are equipped with technologies that enable communication with other vehicles, roadway infrastructure, and nearby road users such as pedestrians and bicyclists. This communication is possible by the unidirectional or bidirectional sharing of data between a CV and other road elements. Data such as vehicle speed, position, weather condition, hazard detection, etc. are retrieved by the sensors installed on the CVs, and such data are exchanged with other road elements. Thus, in a connected environment, all road users benefit at once because of the sharing of data or information retrieved by one component of the system. The benefits could range from the individual to the societal level. Individual benefits could be reliable information about the travel time, road hazards ahead, weather conditions, etc., whereas the societal benefits could include monitoring of highways and infrastructures, efficient design of traffic signals, congestion reduction, etc. With all these perspective benefits of CVT, the challenge is to bring CVs to real-

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world roads and highways. Regardless of the timeline of deployment, prior understanding of the possible barriers to the adoption and usage of technology will inform vehicle developers, industries, policymakers, and agencies to plan for ways to improve public attitude and intention towards adopting the technology.

This study is dedicated to uncovering the barriers to the adoption of CVT by modeling public interest in adopting CVs. In particular, a multivariate ordered probit model of the public intention to ride/use, own/purchase, and recommend CVs is estimated. By modeling these three forms of intention jointly, we explicitly treat the possible correlations across the different forms of CV acceptance caused by some common unobserved factors. To better understand the public barriers to CV acceptance, we account for the unobserved latent factors related to the public attitudes toward data privacy and security issues and the importance of reputation of data manager for CVT. We also account for observed factors related to the socio-demographic, household, and individual travel characteristics in explaining the decision-making process.

The issues of data privacy and security are of keen interest when modeling the acceptance of smart and intelligent technologies that involve connectivity, such as smartphones (Kusyanti, 2022), electronic health care (Dhagarra et al., 2020), online shopping (Vijayasarathy, 2014), and electronic commerce (Eastlick et al, 2006). In the case of CVT, where connectivity is key, data privacy and security are respectively defined as the managerial and technological strength or capacity of the system to protect the data from hacking, unethical sharing, and misuse. Some preliminary past studies (e.g., CAR & MDOT, 2012; Schmidt et al., 2016; Schoettle & Sivak, 2014; Walter & Abendroth, 2020) have concluded that perceived data privacy and security issues could be a major barrier to the acceptance of CVs. In this study, we focus on quantifying and comparing the impact of data privacy and security perceptions in three forms of CV acceptance: intentions to ride, own, and recommend CVs.

In addition to these, we introduce the concept of the importance of reputation of data manager in this study. The data manager is defined as the entity that is responsible for the collection, storage, and use of the data collected from CVs. Because of the need for extensive data management efforts in CVT, we believe the role of data manager is highly important in protecting the privacy and security of data. Assuming that the reputed data manager has public trust and support (as found in Kim et al. (2008) for an electronic commerce service), we hypothesize that the public acceptance of CVs increases when the data management is handled by a reputable organization. Our past study (Acharya & Mekker, 2022) has supported this hypothesis. However, in this study, we broaden the understanding of the importance of reputation of data manager by estimating its impact on the behavioral intentions to ride, own, and recommend CVs.

The modeling framework utilized in this study is illustrated in Figure 1 and follows a two-stage approach. In the first stage, three latent variables—perceived data privacy, perceived data security, and importance of reputation of data manager—are examined using a combination of measurement and structural equation models. The measurement model establishes the connections between observed indicators and underlying latent constructs, while the structural equation model identifies relationships between exogenous variables and latent constructs. The estimated values of these latent variables from the first stage are then used in the second stage. In the second stage, a multivariate ordered probit model is estimated, incorporating two categories of predictors: (1) exogenous variables, which encompass individual and household demographics, socio-economic attributes, and travel-related characteristics, and (2) the three latent variables related to data concerns in CVT, inferred from observed indicators. Although a simultaneous or joint estimation of both models could potentially yield more precise results, a two-stage approach is adopted to mitigate computational complexity. Prior research (e.g., Ben-Akiva et al., 2002) suggests that increasing sample size can effectively reduce measurement errors, and with a sample of 2,221 participants, this study benefits from a robust dataset. Furthermore, Raveau et al. (2010) indicate that the improvement in model fit achieved through simultaneous estimation is relatively minor compared to the significant increase in computational demands, further supporting the choice of a two-stage framework.

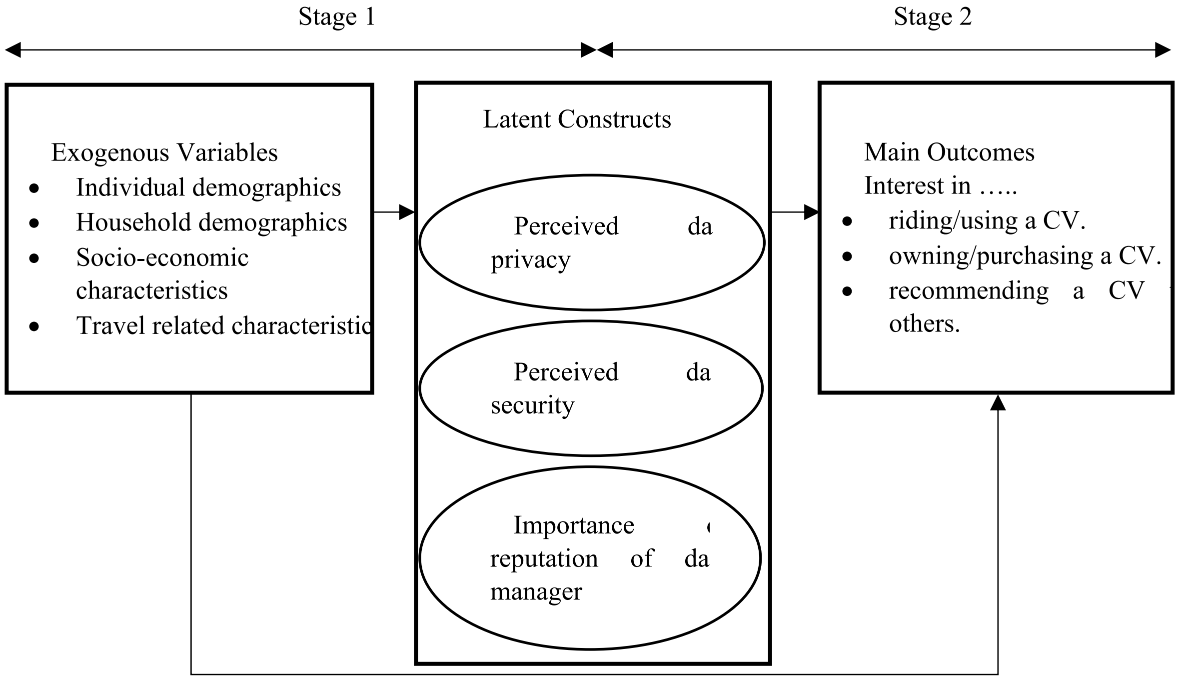

Figure 1: Research modeling framework.

With a limited understanding of public acceptance of CVs, this empirical study primarily contributes to the existing literature in the following three ways.

(a) We consider the general configuration of CVs to model the acceptance behavior. That means CVs are defined as vehicles having full communication abilities (that do not yet exist in the real world) with huge potential benefits in the domain of transportation safety, mobility, and environment. Previous studies have considered the acceptance of some applications of CVT only: uncontrolled unsignalized intersections (Zhao et al., 2021); lane speed monitoring and high-speed differential warnings (Li et al., 2021); emergency electronic brake lights, emergency vehicle warnings, roadworks warnings, and traffic condition warnings (Payre & Diels, 2020); and usage-based insurance policies (Sahebi & Nassiri, 2017). We are aware of two previous studies (Acharya & Mekker, 2022; Walter & Abendroth, 2020) where the general configuration of CVs is considered to model CV acceptance behavior.

(b) We explicitly model the acceptance of CVs in three forms: intentions to ride, own, and recommend CVs. To our knowledge, none of the previous studies have utilized this framework to model the acceptance of CVT. The acceptance models of both previous studies considering the general configuration of CVs (Acharya & Mekker, 2022; Walter & Abendroth, 2020) do not differentiate/consider the intentions to ride, own, and recommend CVs.

(c) We captures taste heterogeneity in CV acceptance across three dimensions—riding, owning, and recommending—by incorporating latent variables that reflect perceptions of data privacy, data security, and the importance of the data manager's reputation. This framework enables a direct comparison of the effects of these latent variables on each form of CV acceptance. Previous studies have explored these factors to varying degrees, with Walter and Abendroth (2020) addressing data privacy concerns and Acharya and Mekker (2022) incorporating all three latent variables into their acceptance models. Expanding on Acharya and Mekker (2022), this study explicitly accounts for taste heterogeneity in the intentions to ride, own, and recommend CVs.

The rest of the paper is structured as follows. The next section outlines the study's methodology, followed by Section 3, which describes the data used in the study. Section 4 presents the analysis, results, and policy implications, while the final section discusses key findings and study limitations.

2. Methodology

This section outlines the methodological framework employed in this study. The analysis of public interest in CV adoption follows a two-stage modeling approach. The first stage involves developing a measurement model to define latent variables associated with perceptions of data-related issues in CVT. This model, along with the structural relationships between latent and exogenous variables, is detailed in Section 2.1. The second stage, discussed in Section 2.2, involves formulating a multivariate ordered probit model to evaluate three distinct forms of CV adoption interest.

2.1 Measurement and structural equation models of latent variables

The measurement model establishes how unobserved latent variables relate to their observed indicators. In this study, various observed items are used to assess three latent factors: perceived data privacy, perceived data security, and importance of reputation of data manager. The relationship between these latent variables and their observed indicators is expressed in Equation 2-1.

$$v_t = \lambda_t F_l + e_l \qquad \text{2-1}$$

where l ε {1, 2, …, L} and t ε {1, 2, …, T} denote the indices of latent variables and observed items, respectively. Here, F_l represents the latent variables, while v_t refers to their corresponding observed indicators. The parameter . λ_t describes the relationship between the observed items v_t and latent variables F_l. The term e_l accounts for measurement errors, which are assumed to follow a standard normal distribution.

The structural equation model defines the influence of exogenous variables on latent variables. In this study, only the effects of exogenous variables on latent factors are considered, as described in Equation 2-2.

$$F_l = B_i Z_i + r_l \qquad \text{2-2}$$

where i ε {1, 2, …, I} is the index of exogenous variables such that Z_i denotes the vector of exogenous variables and B_i represents their respective parameters that explain their relationships with latent variables F_i. r_l is the vector of residuals associated with each latent variable. This error term is also assumed to be standard normally distributed.

2.2 Multivariate ordered probit model

The multivariate ordered probit model extends the traditional probit framework to handle multiple ordered outcome variables simultaneously, while also accounting for potential correlations between them. In this study, the three outcome variables—interests in riding, owning, and recommending CVs—are measured on ordered Likert scales and exhibit interdependencies. Given this structure, the multivariate ordered probit model is well-suited for analyzing these outcomes. Following the formulation outlined by Greene and Hensher (2010) and Washington et al. (2020), the general specification of the model is presented in Equation 2-3.

$$Y_i^* = \beta_i' X_i + \epsilon_i \qquad \text{2-3}$$

where,
i ε {1, 2, …, I} refers to an outcome variable from a set of I.
Y_i^* is an unobserved continuous latent propensity associated with each corresponding outcome variable Y_i.
X_i is a vector of covariates (exogenous and latent variables) associated with the outcome variable Y_i.
β_i is the coefficient vector associated with each covariate X_i for the outcome variable Y_i.
ϵ_i is the error term.

Each ordered outcome Y_i has K ordinal levels, separated by a set of thresholds ($\mu_i^0, \mu_i^1, \mu_i^2, \dots \mu_i^{k-1}, \mu_i^K$), where $\mu_i^0 = -\infty$ and $\mu_i^K = \infty$. The observed value of Y_i is determined by where the latent variable Y_i^* falls within these threshold intervals, as shown in Equation 2-4.

$$Y_i = \begin{cases} 1, \text{if } \mu_i^0 \le Y_i^* \le \mu_i^1 \\ 2, \text{if } \mu_i^1 \le Y_i^* \le \mu_i^2 \\ 3, \text{if } \mu_i^{K-1} \le Y_i^* \le \mu_i^K \end{cases} \qquad \text{2-4}$$

In the probit framework, the error terms ϵ_i are assumed to follow a multivariate normal distribution with mean zero and a variance-covariance matrix that captures the correlations across outcome equations, as specified in Equation 2-5.

$$\epsilon \sim N\left[\begin{pmatrix} 0 \\ 0 \\ \dots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \dots & \rho_{1I} \\ & 1 & \dots & \rho_{2I} \\ & & \dots & \dots \\ & & & 1 \end{pmatrix}\right] \tag{2-5}$$

The off-diagonal elements of Equation 2-5, $\rho_{ii'}$ $(i \neq i')$, represent the correlation between the unobserved components of outcomes i and i'. If these are zero, the model simplifies to independent ordered probit models for each outcome variable.

For a given outcome variable Y_i with K levels, the probability that $Y_i = k$ depends on the covariates, threshold values, and correlation among the error terms. This is expressed in Equation 2-6.

$$\mathrm{P}[Y_i = K] = \int_{z_1}\int_{z_2}\dots\int_{z_K} \varphi(z_1, z_2 \dots z_K, \rho_{11}, \rho_{12}, \dots, \rho_{II})\mathrm{d}z_1, \mathrm{d}z_2, \dots, \mathrm{d}z_K \tag{2-6}$$

The limits of z_1, z_2, …, z_K, are $[\mu_i^0 - \beta_i' X_i, \mu_i^1 - \beta_i' X_i]$, $[\mu_i^1 - \beta_i' X_i, \mu_i^2 - \beta_i' X_i]$, …, $[\mu_i^{K-1} - \beta_i' X_i, \mu_i^K - \beta_i' X_i]$. The function φ (.) represents the multivariate normal density function. Since this integral has no closed-form solution, simulation techniques are employed for model estimation. Finally, the estimated coefficient β_i obtained from Equation 2-6 provide insight into the relationship between covariates and the ordered outcomes. A positive coefficient indicates a higher likelihood of observing the highest level (K) of the corresponding outcome variable Y_i.

3. Data

We designed a stated preference questionnaire survey and distributed it online (from November 2020 to February 2021) to gather the empirical data for this study. In the questionnaire, a CV was defined as *"a vehicle that is capable of two-way communication with other vehicles, infrastructure, the cloud, smart devices, etc."*. The questionnaire aimed to evaluate public perceptions regarding the behavioral intention to adopt CVs and share data within the connected system. For brevity, only the variables used in this study are described in the following sections. For the complete questionnaire, please refer to Acharya and Mekker (2021). Section 3.1 outlines the dependent (outcome) variables, Section 3.2 details individual and household characteristics, and Section 3.3 discusses observed indicators of the latent variables related to CVT data issues.

3.1 Outcome variables

The survey includes three questions designed to assess public interest in CV adoption, each measured on a 7-point Likert scale ranging from 1 (extremely unlikely) to 7 (extremely likely). The specific wording of these questions is as follows:

1. How likely do you think that you would use a CV in the future?
2. How likely do you think that your next vehicle purchase would be a CV?
3. How likely do you think that you would strongly recommend others to use CVs?

Based on how the questions are phrased, they are referred to as intentions to ride, own, and recommend CVs, respectively. After data cleaning, the final sample included 2,221 observations used in the analysis. Figure 2 shows the distribution of respondents' interest across the three types of CV adoption. Overall, more than half of the participants show a positive inclination toward riding, owning, and recommending CVs. Among the three, interest in riding a CV is, on average, higher than the interest in owning or recommending one.

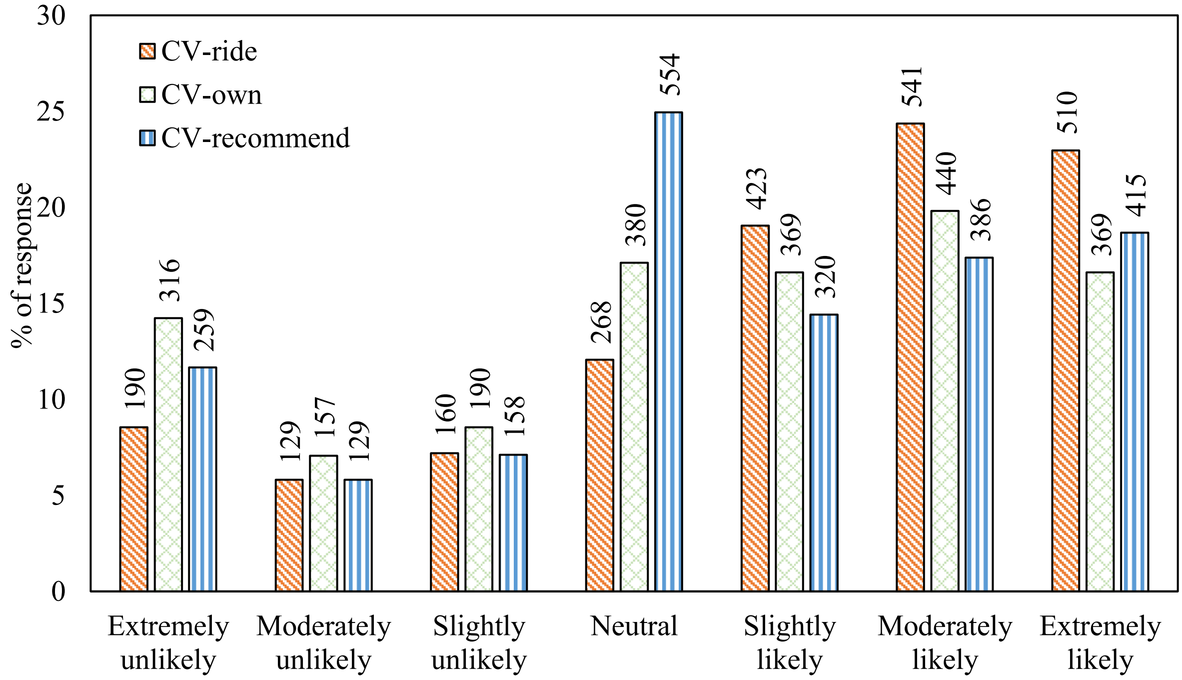

Figure 2: Sample data for public interest in three types of CV adoption-ride, own, and recommend.

3.2 Individual and household characteristics

The individual and household characteristics of the respondents are detailed in Table 1. The sample consists solely of adults, with all participants aged 18 years or older. Over one-third (41.78%) of respondents fall into the 25-44 years age group. The gender distribution shows a higher proportion of females (57.50%) compared to males (42.50%). Regarding race/ethnicity, the majority of the sample (76.63%) identify as white. Nearly half of the respondents (44.26%) report an annual household income between \$25k and \$75k. Educational attainment is nearly evenly distributed, with 38.36% having an undergraduate degree or lower, 38.68% holding a higher education degree, and 22.96% possessing a graduate degree or higher. On average, households consist of 2.169 adults and 0.808 children. A small fraction of the sample (8.96%) are students, while more than half (57.95%) are employed.

Recognizing that the adoption of new vehicle technologies is influenced by individuals' existing travel behaviors, the study incorporates several key travel-related characteristics of the respondents. Slightly less than half of the sample (42.01%) has a typical daily travel time of less than half an hour, whereas the remaining sample is fairly equally distributed in the categories of typical daily travel time between half an hour and one hour (28.59%) and greater than one hour (29.40%). A significant portion of the sample has a driving license (93.20%), and the average driving experience is 24 years. The average household vehicle ownership of the sample is 1.719. More than one-third of the sample (38.14%) has some form of connectivity in their existing household vehicles. In terms of familiarity with CVs and related technology, about half of the sample (51.28%) reports medium familiarity whereas the remaining half splits into low (24.04%) and high (24.7%) familiarity almost equally.

Table 1: Sample data for individual and household characteristics.

Variable	Categorical		Continuous	
	#	%	Mean	SD
Age				
18-24 years	203	9.14		
25-44 years	928	41.78		
45-64 years	625	28.14		
65+ years	465	20.94		
Gender				
Male	944	42.50		
Female	1277	57.50		
Race/ethnicity				
White	1702	76.63		
Others	519	23.37		
Household income (annual)				
< $25k	444	19.99		
$25-75k	983	44.26		
$75-150k	562	25.30		
≥$150k	232	10.45		
Education				
No college degree	859	38.68		
Undergraduate degree	852	38.36		
Graduate degree	510	22.96		
# adults in household (age ≥18 years)			2.169	0.989
# children in household (age <18 years)			0.808	1.064
Student: yes	199	8.96		
Employed: yes	1287	57.95		
Daily travel time				
<30 minutes	933	42.01		
30-60 minutes	635	28.59		
≥ 60 minutes	653	29.40		
Driving license: yes	2070	93.20		
Driving experience (years)			23.964	18.983
Vehicle ownership			1.719	1.022
Connected feature: yes	847	38.14		
Familiarity				
Low/none	534	24.04		
Medium	1139	51.28		
High	548	24.67		

3.3 Indicators of the latent variables related to data issues

Considering that public perceptions of data-related issues in CVT influence behavioral adoption, three latent variables—perceived data privacy, perceived data security, and importance of reputation of data manager—are treated as predictors for the intention to ride, own, and recommend CVs in this study. These unobserved latent variables are measured using eleven indicators or survey items on a 7-point Likert scale. For a detailed explanation of the rationale and development of these indicators, refer to Acharya and Mekker (2022). Table 2 displays the distribution of responses for the indicators of the latent variables. The sample is almost evenly split in terms of perceptions of data privacy and security in CVT, while approximately two-thirds of respondents consider the reputation of data manager to be fairly important (moderately, very, or extremely important) in CVT.

Table 2: Sample data for the indicators of latent variables related to data issues.

Indicators of latent variables	% of observation within each category: extreme unlikely/not important at all (1) - extreme likely/extremely important (7)						
	1	2	3	4	5	6	7
Perceived data privacy							
1. CVs would not collect too much information abo your personal, vehicular, and trip characteristic *(privacy item 1)*	17.6	15.4	13.5	18.1	13.5	12.5	9.05
2. CVs would keep your information in an accura manner in their database. *(privacy item 2)*	5.40	6.89	7.83	15.2	19.4	25.7	19.4
3. CVs would not share your information with oth parties without obtaining your authorization. *(priva item 3)*	13.0	11.0	13.2	15.4	14.2	16.3	16.5
4. CVs would make you feel safe about providing da through the use of a connected vehicle. *(privacy ite 4)*	9.23	9.05	11.7	17.8	17.1	18.6	16.4
Perceived data security							
1. CVs would have sufficient technical capacity to ensu that your data cannot be accessed by a third part *(security item 1)*	8.46	9.46	12.6	14.1	16.3	20.5	18.3
2. CVs would have sufficient technical capacity to ensu that the data you sent cannot be modified by a thi party. *(security item 2)*	7.02	9.14	12.2	15.2	17.2	22.2	16.8
3. CVs would have strong security measures to prote your personal, vehicular, and trip characteristics da *(security item 3)*	7.97	7.88	10.9	13.9	16.7	22.2	20.4
Importance of reputation of data manager							
1. The data manager of CVT should be well know *(reputation item 1)*	1.85	2.21	5.54	12.4	22.2	29.1	26.6
2. The data manager of CVT should have a go reputation. *(reputation item 2)*	0.59	1.35	2.66	7.25	13.3	31.8	42.9
3. The data manager of CVT should be easi recognizable. *(reputation item 3)*	1.08	2.25	4.19	11.8	19.8	30.3	30.3
4. The data management of CVT should be handled by prestigious organization. *(reputation item 4)*	1.40	3.42	4.46	17.0	18.3	26.2	29.0

4. Analyses and results

This section presents the analyses and corresponding results. Sections 4.1 and 4.2 cover the estimated results from the measurement and structural equation models, along with the multivariate ordered probit model. Additionally, Section 4.3 presents a discussion on the pseudo-elastic effects of exogenous variables and the influence of latent variables on the outcome variables, emphasizing their policy implications.

4.1 Estimated measurement and structural equation models

The methodology for estimating the measurement and structural equation models involving latent variables is detailed in Section 2.1. These models are estimated using R (R Core Team, 2022) with the lavaan package (Rosseel, 2012), employing a robust version of the maximum likelihood estimator developed by Yuan and Bentler (2000), known as maximum likelihood estimation with robust standard errors and Satorra-Bentler scaled test statistics (MLM). The estimation results are summarized in Table 3. The models include three latent variables: perceived data privacy, perceived data security, and importance of reputation of data manager.

The measurement model results indicate that 11 indicators effectively define the three latent variables, as evidenced by statistically significant parameter estimates (with large *t*-statistics) for the indicators and latent variables. The overall model fit indices are as follows: chi-square value (degree of freedom = 41) = 198.345 (p-value < 0.001), comparative fit index (CFI) = 0.985, standardized root mean square residual (SRMR) = 0.036, and root mean square error of approximation (RMSEA) = 0.049. These values suggest a good model fit based on the commonly accepted cutoff criteria: CFI ≥ 0.97 (Hu & Bentler, 1999), RMSEA ≤ 0.05 (Browne & Cudeck, 1993), and SRMR ≤ 0.08 (Hu & Bentler, 1999). While a lower chi-square value and higher *p*-value are indicative of a better fit, higher chi-square values are typically observed with larger sample sizes (Bentler & Bonnet, 1980), which is consistent with this study. Based on this measurement model, latent variable scores for each individual are predicted, serving as inputs for the multivariate ordered probit model of CV adoption, discussed in Section 4.2.

After defining the measurement model, the structural equation model is estimated to assess the relationships between exogenous and latent variables. Initially, all individual and household characteristics presented in Table 1 are included as predictors for the latent variables. However, non-significant variables are sequentially dropped, and the final model results are summarized in Table 3. The fit indices for the final structural model are: chi-square value (degree of freedom = 144) = 431.692 (p-value < 0.001), CFI = 0.981, RMSEA = 0.030, and SRMR = 0.026. These values indicate a good, meeting the establish criteria.

The results indicate that older individuals tend to place more importance on the reputation of data manager in CVT, which may be attributed to their generally lower risk-taking behavior, as discussed in socio-technological literature (Brell et al., 2019). For CVT, a reputable data manager is especially valued due to concerns about data privacy and security. Individuals with graduate-level or higher education tend to have more favorable views on data privacy and security in CVT. This could be due to their increased familiarity with such technologies (as noted by Haboucha et al., 2017 in the context of AVs) and their trust in innovative technologies (Liljiamo et al., 2018). However, this group also desires a reputable data manager, likely because of their awareness of current data management practices in CVT.

The possession of a driving license is associated with the higher importance of the reputation of data manager. In addition, individuals with greater driving experience have higher perceived data privacy and security issues. These findings align with the discussions on travel mode switching behavior (Ettema et al., 2016). In fact, people stick to their usual travel mode, and the process of switching travel modes is considered difficult. We consider the lower perception of experienced drivers on data privacy and security and higher demand for a reputable data manager is because of their desire to not switch to a new travel mode or technology.

Individuals with connectivity in their current household vehicles tend to have greater confidence in the data privacy and security aspects of CVT. This heightened confidence likely stems from increased familiarity with CVT, although their demand for a reputable data manager remains significant. This suggests that continued interaction with CVs helps individuals develop trust in data management practices. Additionally, respondents who are unfamiliar with CVT tend to express more concerns about data privacy and security than those with more experience, highlighting the need for CV stakeholders to improve public understanding of the technology. This could involve providing information on efforts to protect data privacy and security, promoting available connected features, and developing marketing strategies to enhance public awareness. Finally, CVT-familiar repondents exhibit a greater desire for a reputable data manager. This is likely because these respondents are unaware of how their data is being collected, stored, and utilized within the CVT ecosystem. To address this, CVT stakeholders should prioritize transparency in data management practices, ensuring that users are fully informed about how their personal data is handled. Ukkuu k

Table 3: Estimation results of measurement and structural equation models.

Variables	Perceived data privac		Perceived data securi		Importance reputation of da manager	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Measurement equation model						
Perceived data privacy						
Privacy item 1	0.564	27.898				
Privacy item 2	0.640	29.797				
Privacy item 3	0.820	54.180				
Privacy item 4	0.857	56.973				

Perceived data security						
Security item 1			0.915	70.596		
Security item 2			0.924	69.384		
Security item 3			0.900	62.891		
Importance of reputation of data manager						
Reputation item 1					0.789	36.307
Reputation item 2					0.730	26.722
Reputation item 3					0.844	40.242
Reputation item 4					0.672	30.281
Structural equation model						
Age: 25-44 years	--	n/a	--	n/a	0.213	2.350
Age: 45-64 years	--	n/a	--	n/a	0.288	3.039
Age: 65+ years	--	n/a	--	n/a	0.344	3.471
Income: ≥$150k	--	n/a	--	n/a	0.168	2.331
Education: Graduate or higher	0.217	3.712	0.206	3.768	0.131	2.157
# children (age <18 years)	0.081	3.463	0.068	3.023	--	n/a
Driving license: yes	--	n/a	--	n/a	0.415	3.850
Driving experience (years)	-0.010	-7.023	-0.008	-5.695	--	n/a
Connected feature: yes	0.250	4.713	0.163	3.294	--	n/a
Familiarity: Medium	0.114	2.766	--	n/a	--	n/a
Familiarity: High	0.663	8.763	0.490	8.002	0.298	4.778

Note: Number of observations = 2221, "--" indicates a non-significant parameter (at 95% confidence interval) that is removed from the model, "n/a" indicates not applicable.

4.2 Estimated multivariate ordered probit model of CV adoption

TThe multivariate ordered probit model of CV adoption is estimated using the mvord package (Hirk et al., 2020) in R (R Core Team, 2020), following the approach outlined in Section 2.2. This model jointly estimates three outcome variables—intentions to ride, own, and recommend CVs—while allowing the error terms to be correlated. The predictors include individual and household characteristics, along with latent variables. Table 4 presents the estimation results. The findings indicate strong correlations (≥ 0.7) among the error components of the three outcomes, suggesting that unobserved factors commonly affect all three forms of CV adoption. The initial model includes all individual and household variables from Table 1, as well as three latent constructs. The model is then refined by gradually dropping insignificant predictors. As a result, only statistically significant estimates are shown in Table 4 and discussed here.

Gender significantly influences the intention to ride CVs, with females showing a lower likelihood. This could be explained by previous findings in the transportation literature: females are less tech-savvy (Kang et al., 2018) and more risk-averse (Wang & Zhao, 2019). Thus, it makes sense that females would have a lower intention to ride CVs, which could be considered risky, especially because of the data issues involved (Walter & Abendroth, 2020). This result is also consistent with the consumer behavior literature, which agrees with the higher likelihood of men towards new experiences and simulations (Vianello et al., 2013) as fully CVs are yet to exist in the real world, thus riding such vehicles is a new experience for individuals.

The effects of race/ethnicity on CV adoption reflect that white individuals are less likely to ride, own, and recommend CVs compared to their counterparts. The understanding of the differences in races in the choice of vehicle technologies is not well known in the literature (Lavieri & Bhat, 2019), but a similar finding is reported by Sharma and Mishra (2020).

Income comes out to be a significant predictor of CV adoption interest, as high-income individuals exhibit a higher likelihood to ride, own, and recommend CVs. This result is as expected (as described in Asmussen et al., 2020) because it is highly likely that CVs will be more expensive than current conventional cars and the adoption of such expensive technology is related to income. In addition, this result aligns with that of Shin et al. (2015), which concludes that potential CV users are optimistic about the benefits offered by the technology but are worried about the associated cost.

Employed individuals show a higher likelihood of riding, owing, and recommending CVs, most probably because of their higher mobility needs (He et al., 2018). It could be expected that employed individuals have a regular need for a vehicle to get to work and, thus, might consider adopting CVs to make their daily travel easy and comfortable by utilizing the benefits offered by the connected features. In addition, a higher likelihood of adopting CVs by employed individuals could be justified by their need to get rid of routine commute delays (Asmussen et al., 2020).

Having a driving license exhibits a higher likelihood of riding and recommending CVs, but an increase in driving experience decreases the propensity to adopt CVs in all three forms. This could be explained by the travel mode captivity of experienced drivers to conventional cars (Ettema et al., 2016). In addition, the enjoyment that experienced drivers might get from manually controlling conventional cars (Haboucha et al., 2017) might explain the reasoning behind their lower preference for CVs, considering that the control of CVs should be made based on the information and instruction provided by the CVT controller. Similarly, higher household vehicle ownership is linked to a lower intention to own and recommend CVs, which could be associated with the burden of having to abandon the already-owned household vehicles (Acharya & Humagain, 2022).

Having a form of connected features in existing household vehicles shows a greater likelihood to ride, own, and recommend CVs. In addition, the increase in familiarity with CVT tends to increase the likelihood of riding, owning, and recommending CVs. Though the actual CV usage intention is developed only when users have real experience with the technology, we consider these results as a positive sign toward the acceptance of CVs because the CVT familiar users (though not to full connectivity) have a positive perception about riding, owning, and recommending CVs. This calls for the effort of CVT stakeholders in improving the familiarity and experience of the public with the connected features and applications. This can be accomplished by promoting the available connected features, creating new marketing strategies to educate the public about these features, offering test-drive opportunities for CVs, and so on.

All three latent variables related to CVT data issues exhibit significant associations with all three forms of CV adoption. In other words, higher CV adoption—in terms of riding, owning, and recommending—is expected for individuals having positive perceptions of data privacy, data security, and the reputation of data manager. This finding is explained by the theory of perceived risk developed by Cox (1967), which states that the adoption of new technology is dependent upon the risks involved. Numerous previous studies have verified this theory in the adoption of new technologies, including vehicle technologies. For example, Zhang et al. (2020) found safety and privacy risks as barriers to the acceptance of AVs. In the case of CVT, Walter and Abendroth (2020) asserted that data privacy concerns and risks lower the behavioral intention to adopt CVs. Although the impact of these three latent variables on the acceptance of CVs is known from our previous study (Acharya & Mekker, 2022), the impact of each latent variable on the intention to ride, own, and recommend CVs is supplemented by this study. The comparative impacts of each latent variable on each form of CV acceptance are presented in Section 4.3.2.

Table 4: Estimated multivariate ordered probit model of CV adoption.

Variables	Intention to ride		Intention to own		Intention to recommend	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Individual and household characteristics						
Gender: Female	-0.103	-2.941	--	n/a	--	n/a
Race/ethnicity: White	-0.113	-2.088	-0.115	-2.155	-0.204	-3.732
Income: $25-75k	--	n/a	0.140	3.181		
Income: $75-150k	--	n/a	0.105	2.086		
Income: ≥$150k	0.314	3.734	0.428	4.845	0.276	3.204
Employed	0.189	3.694	0.118	2.307	0.132	2.556
Driving license: yes	0.176	2.366	--	n/a	0.171	2.338
Driving experience (years)	-0.006	-3.891	-0.004	-3.028	-0.009	-6.103

Vehicle ownership	--	n/a	-0.045	-2.587	-0.044	-2.438
Connected feature: yes	0.440	8.161	0.602	11.132	0.451	8.294
Familiarity: Medium	0.382	6.892	0.407	7.229	0.302	5.292
Familiarity: High	0.740	9.679	0.816	10.678	0.779	9.943
Latent variables						
Perceived data privacy	0.313	5.688	0.294	5.341	0.410	7.416
Perceived data security	0.231	4.570	0.230	4.461	0.249	4.816
Importance of reputation of da manager	0.150	6.084	0.078	3.069	0.144	5.603
Thresholds						
Extremely | Moderately unlikely	-1.308	-13.620	-0.871	-10.372	-1.360	-14.205
Moderately | Slightly unlikely	-0.885	-9.565	-0.498	-6.057	-0.989	-10.698
Slightly unlikely |Neutral	-0.498	-5.472	-0.137	-1.681	-0.646	-7.134
Neutral | Slightly likely	-0.010	-0.106	0.462	5.690	0.294	3.237
Slightly | Moderately likely	0.662	7.268	1.049	12.548	0.850	9.201
Moderately | Extremely likely	1.582	17.061	1.899	21.896	1.643	17.272
Correlations						
Intention to ride	1.000	n/a	0.741	<0.001	0.722	
Intention to own			1.000	n/a	0.749	
Intention to recommend					1.000	n/a
Goodness of fit measures						
Number of observations	2221					
Log-likelihood of null model	-21136.28					
Log-likelihood of full model	-18836.77					

Note: "--" indicates a non-significant parameter (at 95% confidence interval) that is removed from the model, "n/a" indicates not applicable.

4.3 Policy analyses and implications

The estimates presented in Table 4 can be interpreted by examining the sign (positive or negative) of the coefficients. A positive sign suggests an increased likelihood of the highest level of interest (i.e., "extremely likely") or a decreased likelihood of the lowest level of interest (i.e., "extremely unlikely") for the corresponding outcome variable. However, these estimates alone do not fully capture the direction and magnitude of the effects that the independent variables have on the outcome variables. To provide a more comprehensive interpretation of the model results in terms of policy implications, we calculate the pseudo-elasticity effects of exogenous variables and assess the influence of latent variables on choice probabilities, in line with the approach of Piras et al. (2021). The findings are discussed in Sections 4.3.1 and 4.3.2, respectively.

4.3.1 Pseudo-elasticity effects of independent variables on CV adoption interests

Pseudo-elasticity effects refer to the change in the probability of choosing each level of an outcome variable resulting from a change in an independent variable. In this study, we calculate the aggregate pseudo-elasticity effects using Equation 4-1.

$$\Delta P(Y_{ik}|X_i, X_i') = \frac{1}{\mathrm{N}}\sum_{n=1}^{N}[\,P(Y_{ik}|X_i') - P(Yy_{ik}|X_i)] \qquad \text{4-1}$$

where, $\Delta P(Y_{ik}|X_i, X_i')$ represents the change in the choice probability for level k ε {1, 2, …, K} of an outcome variable Y_i when the set of independent variables changes from X_i to X_i'. To compute this, only one independent variable of interest is altered in the set X_i, while the other variables are held constant to form X_i'. The change in choice probability is calculated for each individual n ε {1, 2, …, N}, and the results are averaged across the entire sample of N individuals.

For continuous independent variables within X_i, the change is made by increasing or decreasing the variable by a specific percentage (e.g., 20%), while keeping all other variables constant. For categorical variables, the change is made by modifying the levels of the categories of interest, with the other variables remaining the same. Although multiple changes in independent variables could be considered, for simplicity, we focus on one change per variable, and the results are summarized in Table 5. Additionally, for brevity, we calculate the change in choice probabilities only for the extreme levels ("extremely unlikely" and "extremely likely") as well as the middle level ("neutral"), even though each outcome variable has seven possible levels. It is important to recognize that changes in independent variables influence the outcome variables both directly and indirectly through latent variables. These indirect effects are also incorporated into the calculation of the pseudo-elasticity effects.

The pseudo-elasticity values in Table 5 allow for comparison of the impact each independent variable has on different forms of CV adoption. The percentage changes in Table 5 represent the increase or decrease in the aggregate probability of selecting a particular level of an outcome variable when an independent variable is modified. For example, when all individuals in the sample are assumed aged 65 or older, the probability of being in the "extremely unlikely" category for riding a CV decreases by 0.14%. While all pseudo-elasticity effects for both independent and outcome variables are presented in Table 5, only the more substantial effects are discussed here.

Income exhibits a large impact on the choice probability of the levels of outcome variables. When all individuals are considered to have an annual household income greater than \$150k, the probabilities of being in the "extremely likely" category for intentions to ride, own, and recommend CVs increase by 6.85%, 7.60%, and 7.92%, respectively. This result aligns with the previous findings of public concern over the cost of CVs (Shin et al., 2015). Among the three outcome variables, income has the highest sensitivity to CV owning intention. Similarly, when all individuals are assumed to have a graduate degree or higher, the probabilities of being "extremely likely" to ride, own, and recommend CVs increase by 2.15%, 1.52%, and 2.05%, respectively.

Other independent variables that have large impacts on the choice probability of outcome variables are the availability of connected features in existing household vehicles and familiarity with CVT. When all individuals were assumed to have some form of connected features in their household vehicles, the probabilities (extremely likely) of riding, owning, and recommending CVs increase by 7.07%, 7.21%, and 5.93%, respectively. Similarly, these probabilities increase by 20.91%, 18.28%, and 19.25%, respectively when all the individuals were considered to have a high familiarity with CVT. These higher sensitivities of connected features and familiarity with CVT on CV adoption further support our earlier discussion about the initiatives that CV stakeholders could follow to improve public acceptance of CVs.

4.3.2 Impact of latent variables on CV adoption interests

Calculating the pseudo-elasticity effects of latent variables is not appropriate because it does not make sense to arbitrarily increase the values of latent variables by a certain percentage. Instead, to examine the impact of latent variables on three forms of CV adoption, we segment the sample into three equal terciles based on the values of these latent variables. This results in segments representing low, medium, and high perceptions of data privacy, data security, and importance of reputation of data manager. For each segment, we calculate the choice probabilities of all outcome levels. However, for simplicity, we present the choice probabilities for the two extreme levels (i.e., "extremely unlikely" and "extremely likely") as well as the middle level (i.e., "neutral") for each latent variable, as shown in

Figure 3, Figure 4, and Figure 5. The figures illustrate the impact of latent variables on each form of CV adoption. For example, the probability of selecting the "extremely likely" intention to use a CV is 46% for the segment with a high perception of data privacy, compared to 17% for the medium perception and 6% for the low perception segment. The values from the figures also indicate that latent variables have a stronger effect on the intention to use a CV than on the intentions to own or recommend one. When comparing the effects of latent variables on CV adoption, the overall sensitivity to data privacy and security perceptions across all three types of CV adoption is slightly higher than the impact of importance of reputation of data manager. It is important to note that these sensitivities reflect the direct impacts of latent variables on the outcome variables, without accounting for possible indirect effects (such as the indirect influence of data manager reputation on CV adoption through perceptions of data privacy and security, as found in Acharya and Mekker (2022)). Therefore, a careful interpretation of the estimated impacts of latent variables on the intentions to ride, own, and recommend CVs is warranted.

Table 5: Pseudo-elasticity effects of independent variables on CV adoption interests.

Independent variable	Change in independe variable	Outcome variable	Extremely unlikely	Neutral	Extremely likely
Age	All individuals are 6: years	Ride	-0.14%	-0.09%	0.37%
		Own	-0.12%	-0.04%	0.17%
		Recommend	-0.16%	-0.12%	0.31%
Gender	All individuals are fema	Ride	0.40%	0.23%	-1.07%
		Own	n/a	n/a	n/a
		Recommend	n/a	n/a	n/a
Race	All individuals are white	Ride	0.28%	0.17%	-0.59%
		Own	0.46%	0.11%	-0.47%
		Recommend	0.64%	0.32%	-0.86%
Income	All individuals ha income > $150k	Ride	-3.22%	-1.74%	6.85%
		Own	-6.18%	-1.71%	7.60%
		Recommend	-3.70%	-1.52%	4.92%
Education	All individuals ha graduate or higher degree	Ride	-1.30%	-0.54%	2.15%
		Own	-1.76%	-0.24%	1.52%
		Recommend	-1.88%	-0.56%	2.05%
# of children	All individuals have o more child in the househol	Ride	-0.47%	-0.20%	0.89%
		Own	-0.68%	-0.12%	0.71%
		Recommend	-0.72%	-0.23%	0.90%
Employment	All individuals a employed	Ride	-1.24%	-0.33%	1.34%
		Own	-1.12%	-0.01%	0.61%
		Recommend	-1.07%	-0.06%	0.69%
Driving license	All individuals ha driving license	Ride	-0.23%	-0.08%	0.30%
		Own	-0.05%	0.00%	0.03%
		Recommend	-0.23%	-0.09%	0.25%
Driving experience	All individuals ha driving license and th driving experience increas by 5 years	Ride	0.40%	0.17%	-0.83%
		Own	0.74%	0.11%	-0.75%
		Recommend	0.87%	0.22%	-1.06%
Vehicle ownership	All individua household vehic ownership increases by on	Ride	n/a	n/a	n/a
		Own	0.81%	0.12%	-0.80%
		Recommend	0.66%	0.18%	-0.77%
Connected features	All individuals have sor connected features in th vehicles	Ride	-4.17%	-2.04%	7.07%
		Own	-7.90%	-1.66%	7.21%
		Recommend	-5.63%	-1.93%	5.93%
Familiarity	All individuals have hi familiarity with CVT	Ride	-6.63%	-5.73%	20.91%
		Own	-11.21%	-5.50%	18.28%
		Recommend	-9.46%	-8.51%	19.25%

Note: "n/a" indicates not applicable.

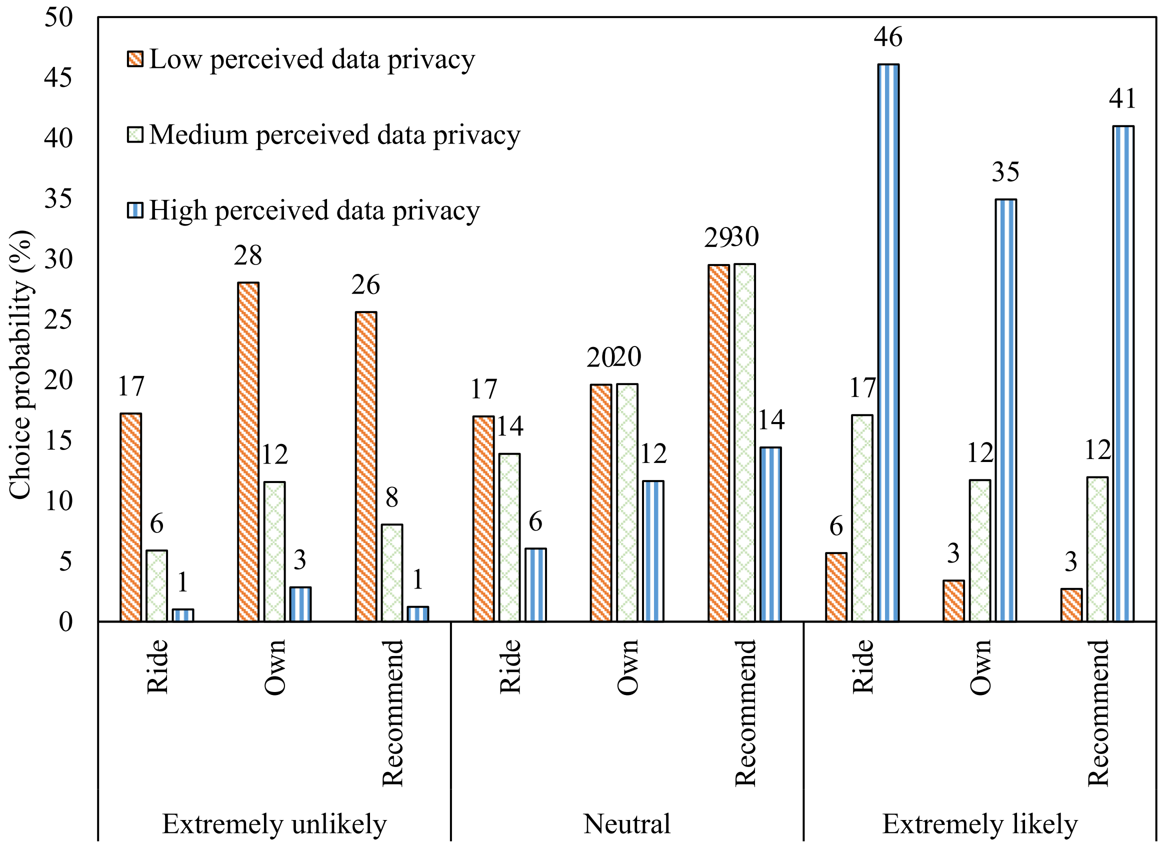

Figure 3: CV adoption interests for various levels of data privacy perception.

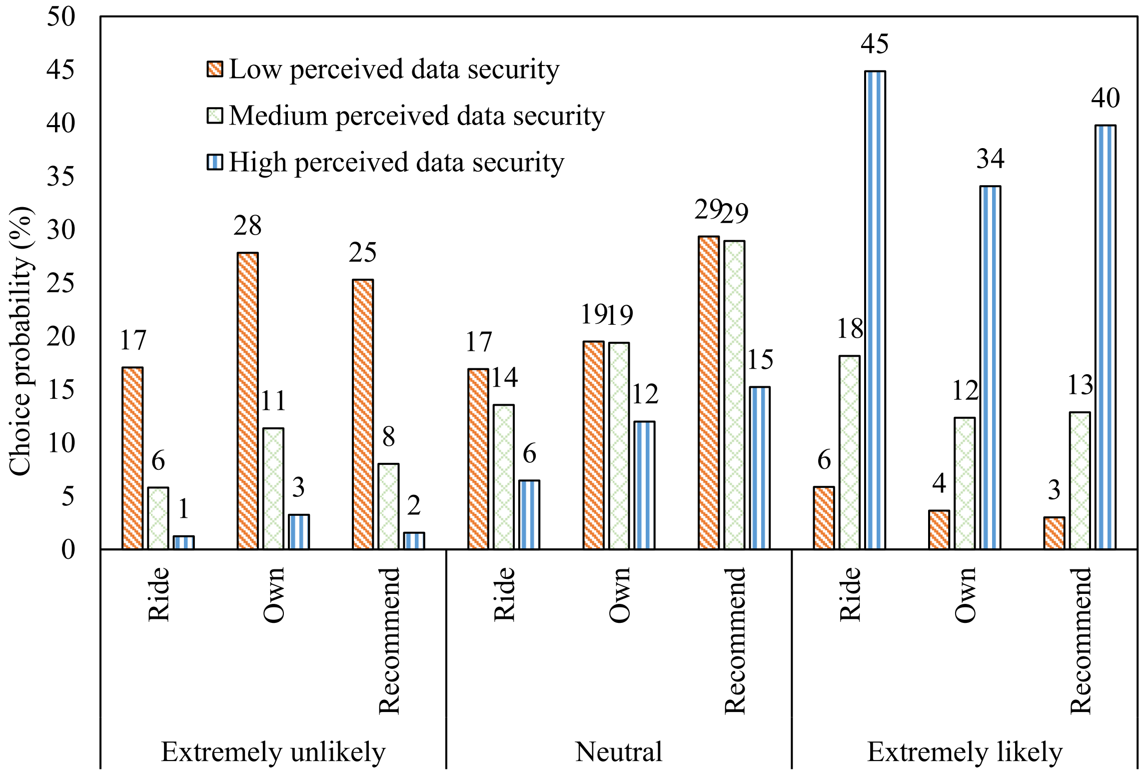

Figure 4: CV adoption interests for various levels of data security perception.

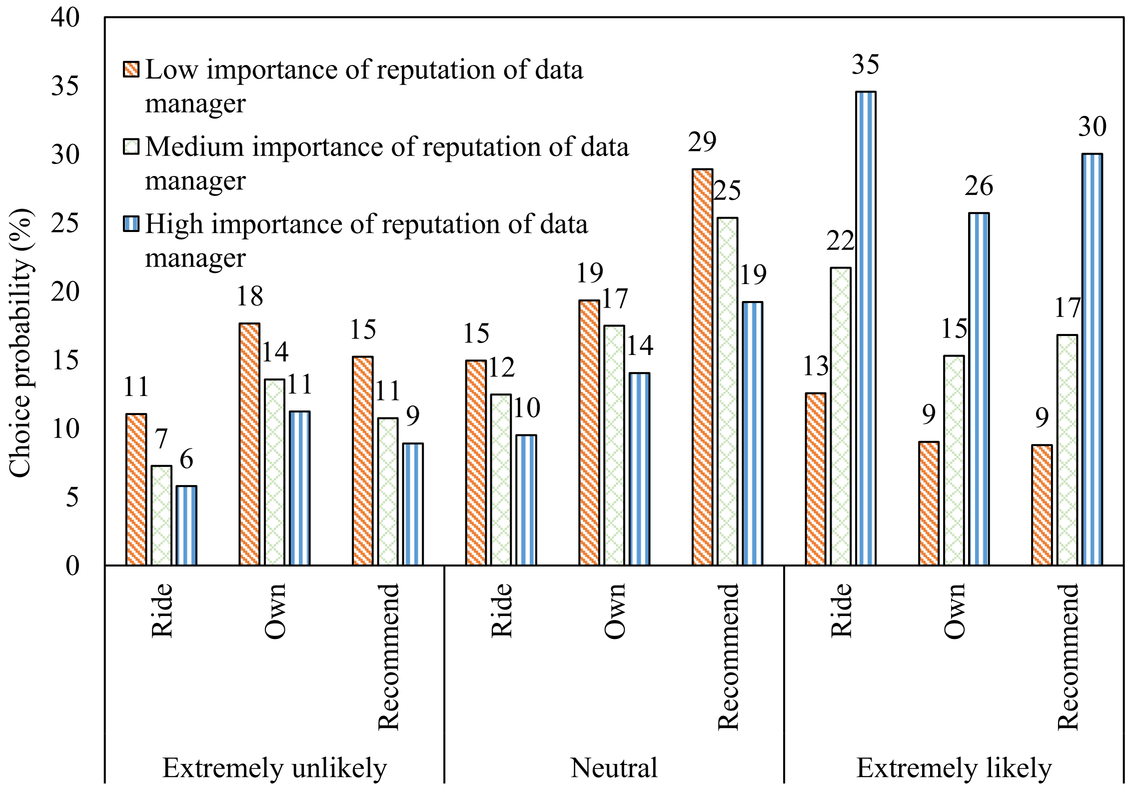

Figure 5: CV adoption interests for various levels of the importance of reputation of data manager.

5. Conclusions and recommendations

Given that previous studies have identified data concerns as a major barrier to CV adoption, this study jointly models individuals' intentions to ride, own, and recommend CVs. The model incorporates a range of exogenous variables, including individual and household socio-demographic characteristics, along with three latent variables related to data concerns: perceived data privacy, perceived data security, and importance of reputation of data manager. By estimating these outcomes jointly, the model explicitly captures the correlation among the adoption intentions. As shown in Table 4, the results confirm that unobserved factors influencing these three forms of CV adoption are strongly correlated (correlations > 0.7). The data for this analysis were obtained from a nationwide survey conducted in the US during 2020–2021.

The estimation results show that several individual and household socio-demographic characteristics—age, gender, income, employment, education, and number of children—and some other travel-related characteristics—driving license, driving experience, household vehicle ownership, availability of connected features in household vehicles, and familiarity with CVs—impact the different forms of CV adoption either directly or indirectly through the latent variables related to the CV data issues. The estimates show that while all three latent variables have a positive impact on all forms of CV adoption, in general, they have the greatest impact on intention to ride compared to intentions to own and recommend.

Additionally, we explore several policy implications through our model estimates. First, we assess the pseudo-elasticity effects by altering the independent variables and observing the resulting impacts on the outcome variables. The findings highlight that different independent variables influence the outcome variables to varying degrees. Overall, the availability of connected features in household vehicles and familiarity with CV technology have the most significant influence on all forms of CV adoption, compared to other individual and household socio-demographic factors. Second, we examine the impact of latent variables on the outcome variables by dividing the sample into three segments based on the values of these variables. When analyzing the effects of latent variables on CV adoption, we find that the influence of data privacy and security perceptions on all froms of CV adoption is slightly stronger than the impact of the importance of repuration of data manager.

Based on the study findings, we put forward the following recommendations to the vehicle developers/manufacturers, transportation agencies, and policymakers:

a) Individual data privacy rights: The privacy of the data collected by CVs needs to be handled properly because such data might consist of individually identifiable information, with which the public is wary. The provision of informing the users about what data are collected from the vehicles, how they are anonymized, how they will be stored, and how they will be used along with the requirement of prior consent could assist in protecting individual data privacy rights and improving perceptions of data issues.
b) Legal framework for data management: The way vehicle companies are managing the data collected from the CVs needs to be brought under the legal framework. Provision of the legal guidelines on the type of data that could be collected, the way of anonymizing the data, the technological requirement of the data storage system to maintain data security, and ways data could be used for traffic operation, management, studies, etc. could enhance public confidence in data privacy and security. In addition, the questions of liability and accountability regarding data privacy and security need to be incorporated legally.
c) Education, awareness, and marketing: Educating and informing the public about the individual and societal benefits of CVs could help develop positive public attitudes about adopting CVs. Several marketing strategies, such as CV test-drive opportunities, could help to increase public familiarity with the technology. Discounted insurance premiums for vehicles with connected features could attract financially-aware customers. These and other strategies could ultimately embrace public CV adoption interests.

Finally, we identify three limitations in this study that could be addressed through further research. First, the distinction between CVs and AVs may not be clear to all respondents. Although we provided definitions and explanations of CVs in the questionnaire, there is a possibility that respondents did not fully engage with or comprehend the provided information, especially in an online survey setting. We could minimize this issue by conducting interview surveys instead. Second, we limited the study to three CV data-related variables as latent, but other attitudinal factors, such as technology savviness, travel attitudes, and environmental concerns, could also influence the adoption of different types of CVs, as found by Haboucha et al. (2017) and Nazari et al. (2018) in the case of AVs. Third, more realistic estimates could be obtained by replacing the two-stage modeling strategy used in this study with the simultaneous estimation method proposed by Bhat (2015), though this would increase the computational burden.

6. Declaration of Interest

None

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