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Achieving Inclusive Transportation: Fully Automated Vehicles with Social Support*

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Abstract

We provide quantitative evidence of whether a representative sample of the newly introduced fully automatic vehicles (FAVs) are inclusive. We answer this question by examining FAV demand with a focus on natural disaster victims—people who have become physically or mentally challenged due to severe disaster damage, including those with post-traumatic stress disorder. We investigate whether the fear of natural disasters, social support, environmental concerns, the fear of potential accidents, and merits regarding FAVs are motivators of, or hindrances to, purchasing intentions of FAVs. To do so, we acquire a unique dataset covering disaster victims with traumatic disaster damages (12,286 observations in total) and people without such experiences (57,105 observations in total). Then, we construct a multigroup structural estimation model to estimate FAV demand. We conduct estimations of latent and socioeconomic variables which demonstrate people's attitudes. Our findings show that the social support of family, friends, and local authorities is a crucial factor in motivating disaster victims to appreciate and purchase FAVs. The positive impact of social support on appreciating/purchasing FAVs can offset the negative impacts of a fear of natural disasters and accidents, thus enabling more people to enjoy FAVs.

Keywords: Autonomous vehicle; Automated transport; Self-driving car; Emerging transport modes; Mobility on–demand; Demand Estimation
JEL classification: L62, Q48, Q55, Q58

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1 Introduction

1.1 Research Motivation

The introduction of new transportation modes demands *inclusiveness*, which indicates the inclusion of the socially vulnerable ([90]). Excluding the vulnerable would result in transport disadvantages, transport poverty, and an increase in the risk of social exclusion, widening the disparities between those who belong to the vulnerable and the general public.

However, despite the soaring attention paid to the potential benefits, whether such modes are inclusive remains unanswered. Previous works express concern on the transportation exclusion problems faced by low-income individuals, which is a crucial problem also addressed in [53], [77]. However, the discussions on the social exclusion of those who are not allowed to drive, regardless of their sociodemographic status, due to their physical or cognitive disabilities remain inadequate. Research gaps persist in whether these people can fully enjoy the newly introduced (or planned to be introduced) modes. Among several newly introduced transportation modes, this study focuses on fully-automated vehicle (FAV) technology – which do not require human operators and thus can serve the vulnerable – which has the potential to fundamentally alter transportation systems by reducing fatal road accidents, provide critical mobility to elderly and disabled people, increase road capacity, save fuel, and reduce emissions ([4]).

1.2 Previous Works and Our Contribution

The aforementioned potential benefits have allowed FAVs to consistently capture the attention of the public and researchers. Recent studies identify ways to extend the market share of FAVs and autonomous vehicles (AVs) by understanding consumer choices ([97], [29], [8]), investigating the diverse perceptions of F/AVs ([19], [13], [15], [69], [32]), and identifying the demand for various types of AVs such as shared AVs (SAVs) ([85], [22], [47]). Most recent strands of literature argue that a high level of environmental consciousness, a high education level, younger age, and a higher level of income are positively correlated with consumers' willingness-to-buy (WTB) and willingness-to-pay (WTP) of F/AVs.

Thus far, few studies have investigated whether socially vulnerable classes would adopt and appreciate FAVs. A notable exception is [17], which focuses on the role of AVs for elders in overcoming hindrances to travel. This is because older adults are likely to experience transport disadvantages, transport poverty, and the risk of social exclusion because their physical or cognitive disabilities might prevent them from using FAVs ([76]). While such findings are worthwhile, in this study, we focus on the aspects of social exclusion. Specifically, what is the likely outcome for individuals experiencing physical or cognitive disability, regardless of age, income level, gender, and other sociodemographic characteristics? Simply put, people with cognitive impairments might find it difficult to operate new technologies and to override controls ([64]).

In this study, we focus on *disaster victims* who have experienced traumatic damages due to the natural disasters, which include but are not limited to: the loss of family and friends, severe injuries, and post-traumatic stress disorder (PTSD) and are thus likely to have temporarily or permanently lost the ability to drive. Would factors closely correlated with the public acceptance of F/AVs still be crucial for the disaster victims to accept/appreciate F/AVs? By answering this question, this study contributes to both understanding demand patterns and the provision of policies designed to encourage inclusive transportation modes, which goes beyond discussions on FAVs.

Additionally, we follow numerous previous studies that report that natural disaster experiences increase risk perceptions ([27], [23], [9], [33]) and that increased risk perceptions discourage victims from accepting new technology ([50], [11]). Such trends can also be found in the field of transportation (which is usually represented by a new mode choice or driving behavior) ([57], [58], [2]) Among these studies, previous works on FAVs report that increased risk would hinder the use and adoption of FAVs ([14], [94], [93]).

1.3 Research Hypothesis

Referring to the findings of and gaps in previous works, we set our main research questions as follows: If disaster victims are reluctant to employ FAVs, then would support from family, friends, local authorities, and the government encourage them to choose or appreciate FAVs? Previous works argue that fears about new technology among disaster victims would hinge substantially on social support, namely support from family, friends and local authorities (governments). Thus, social support may decrease perceived risks ([86], [24], [66]). If that is the case, whether social support can encourage the disaster victims to adopt new technologies is also worth investigating.

Additionally, we examine whether disaster victims are reluctant to choose FAVs because FAVs may take control of the drivers in times of an accident. The previous works often witness such trends, which mention that the disaster victims are substantially concerned about controllability in protecting themselves ([27], [38]).

1.4 Brief Introduction on Methodology

We conduct a large-scale survey of over 100,000 respondents in Japan. We first ask questions on disaster experiences, such as whether a respondent is a disaster victim and as a result has experienced PTSD, physical injuries, mental damages, severe losses of private property and the loss of friends/family members. Because we select Japan as our study area, which is particularly vulnerable to natural disasters because of its climate and topography with experiences of countless earthquakes, typhoons, and other types of disasters, our data allow us to obtain a sample that includes over 10,000 observations of disaster victims. This setting allows our results to be more realistic because losing the ability to drive due to a disaster may require multiple natural disaster experiences, which are likely to happen in Japan. Thus, our setting eliminates the necessity of soliciting the time and name of a specific disaster that caused physical and mental damages to the respondent. Next, we additionally ask questions regarding the purchasing decisions (willingness-to-buy, WTB) and perceived value of FAVs (hereafter, FAV values), individual characteristics such as income, gender, age, environmental concerns, and opinions on the advantages of and concerns regarding FAVs.

Referring to the extensive literature reviews on the factors that are crucial for FAV demand, we construct four empirical models that answer our research questions. After filtering out the respondents who were unaware of FAVs, lacked environmental concerns or failed to provide sociodemographic details, we build models for full samples (69,391 observations) and three sample groups: those without disaster experiences (Group 1, 57,105 observations), disaster victims, who are classified according to the type of disaster experience (Group 2, 7,853 observations, and Group 3, 4,433 observations) to compare coefficients across the sample groups. We graphically illustrate our research in Figure 1. We first identify attitudes with respect to behaviors and estimate the relationship between attitudes (along with socioeconomic variables) and decisions.

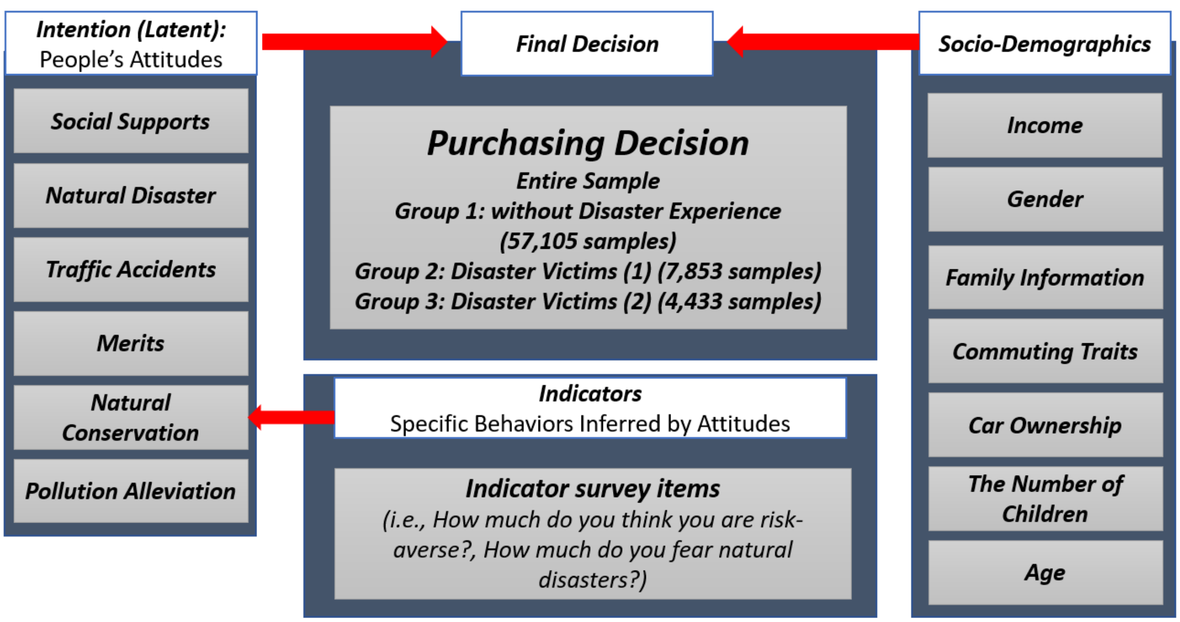

Figure 1: Study Structure

1.5 Paper organization

We further discuss how to encourage disaster victims to gradually accept and appreciate FAVs. The remainder of this paper is structured as follows. Section 2 provides background information on the industry and policy. The data and model are presented in Sections 3 and 4. Section 5 reports the empirical results. Section 6 discusses our findings and provides policy implications. Section 7 concludes the paper.

2 Backgrounds

In this section, we first explain what an FAV is, then briefly introduce the governmental efforts of Japan in achieving inclusive transport by focusing on FAVs.

2.1 Fully Autonomous Vehicles (FAVs)

AVs have different levels of automatic operation as presented in Figure 2. A system generally unconditionally performs all driving operations at level 5 (fully automated, or FAV) and has not yet been realized as of 2021. Currently, consumers cannot select the specific technology or devices to integrate with their new cars when purchasing level 1 and 2 AVs.[1] For high and full levels of automation (levels 4 and 5), cars are expected to pass driving qualification tests, which inspect whether obligatory automation-related equipment and accessories are equipped. As illustrated in Figure 2, the Society of Automotive Engineers (SAE) has defined different levels of automated functionality, ranging from no automated features (level 0) to full automation (level 5 — commonly referred to as autonomous, self–driving or driverless vehicles).

2.2 FAVs and Social Exclusion

The Japanese government announced that FAVs can create mobility opportunities to socially excluded people who are unable to drive, such as the elderly (those with noticeable

[1] We refer to the year 2021.

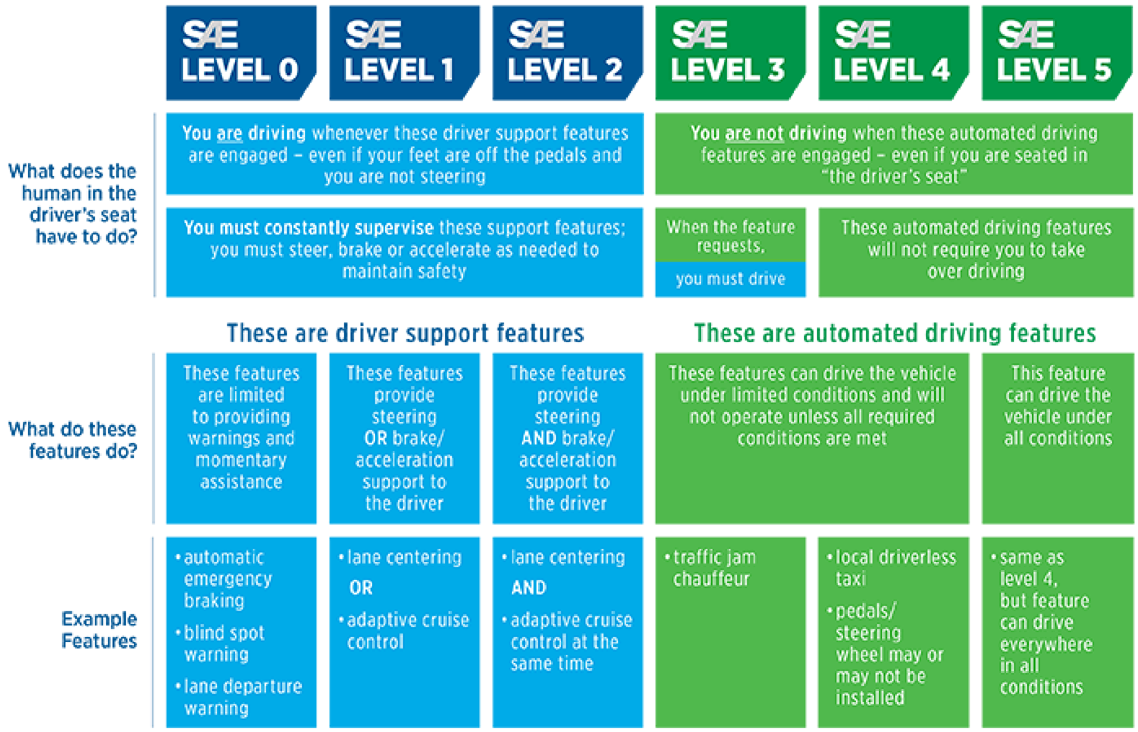

Figure 2: Summarized Explanations of AV Technology by Level.
Source: Society of Automotive Engineers International (2021, Accessed August 4, 2021)

problems in driving capacities) and physically/mentally challenged people. As mentioned in Section 1.2, such traits are evident among the disaster victims who are afraid of losing *control*, the ability to protect themselves, while they are inside the FAVs. To do so, the Japanese Government–along with FAV manufacturers– needs to show *social assurance* that FAVs are safe ([56], [91]) in order to accommodate for disaster victims. Such efforts by the Japanese Government to pursue social assurance of FAVs, and their adoption by socially-excluded people, motivate our study to focus on Japan, with the disaster-related characteristics mentioned in Section 1.2. Meanwhile, because such efforts are increasing in other countries, our implications can be extended to similar production and legislative efforts in other countries trying to pursue FAVs.

The efforts of the Japanese government can be classified into two types; encouraging technological developments and the inclusion of socially vulnerables in the legislation scheme. First, to motivate technological developments that improve the vulnerable in using FAVs, the Japanese Government has emphasized the necessity of developing technologies capable of resolving social problems by listening to the voices of various stakeholders, including those *who find it challenging to speak up socially.* Through cabinet meetings and policy guidelines, the Japanese Government has urged automotive manufacturers to develop technologies that can assist socially vulnerable people. An example includes developing systems ensuring the safety of FAVs in times of accidents to the vulnerable such as the elderly, disabled, pregnant women, and so on. [2]

Second, the Japanese Government announced that it would actively promote FAVs as the representative inclusive transportation mode, encompassing those who are socially excluded. On March 29, 2019, the Japanese cabinet announced that the country's entire transportation system should pursue a transition to be more flexible to change and respond as FAV technology evolves, thereby fully realizing the benefits of FAVs. The transition should not only cover improving efficiency based on existing socially accepted objectives (e.g., improving convenience and preventing accidents) but also realizing new value created by diversifying the objectives themselves (by including socially vulnerable people in the policy goals) and resolving problems such as transport disparity and social exclusion.

3 Data

As mentioned in Section 1, disaster victims may refuse to adopt FAVs regardless of social support due to a fear of new technology adoption, and uncertainty of accidents arising from a loss of direct control of the vehicle. If such concerns outweigh the reduction in risk due to social support, disaster victims would not choose or appreciate FAVs. In this case, a valid empirical strategy is to compare the levels of the psychometric variables while allowing correlations between them; we seek to design empirical strategy successfully

[2] We refer to the national report published by the Japanese Government Cabinet Secretariat, "Social Principles of Human-Centric AI," and the public report entitled "SIP Automated Driving for Universal Services (SIP-adus) R&D Plan" published by New Energy and Industry Technology Development Organization (NEDO). Both documents were accessed on August 17, 2021.

does both.

We first conducted an online survey in Japan from November 24 to December 5, 2017. The survey was administered to individuals aged 18 and older in Japan. We randomly selected respondents while maintaining gender and age distributions of the respondents similar to those of the Japanese population. [3] Consequently, we had 100,810 respondents. To assess the sample representativeness of the survey, we present the distribution of socioeconomic variables of the survey and Japanese Census data in Appendix Table A1. We find that there are slight differences in gender and education levels between our survey and Japanese Census data. Before the large-scale survey started, a pre-survey was administered to calibrate the questionnaires. In what follows, we explain our data by dividing the explanation into the areas of 1) identifying disaster victims, 2) FAV-related questions, 3) socioeconomic variables and 4) latent variables.

3.1 Identifying Disaster Victims

To proceed, we first ask whether our respondents had experienced physical/mental damages due to natural disasters. If so, we then asked the respondents to look into a list of disaster damages, allowing the respondents to choose any item that they have experienced, as illustrated in Table 1, which shows the number and the portion of observations associated with each item in the first column. Among the items listed in Table 1, we place particular emphasis on those that are likely to be a 'traumatic experience' which covers experiences are likely to be closely related to physical and mental problems such as anxiety, major depression, nightmares, hypervigilance, and panic attacks associated with trauma-related stimuli, according to previous works in the field of medicine ([46], [61]).

Respondents were allowed to check multiple items. For example, a respondent can check both 'Severe Health Problems' and 'Severe Injury'. Summing up the findings from the previous works aforementioned, we denote the following as 'traumatic experiences':

[3] Such a process was possible as we employ an internet survey conducted by Nikkei Research Inc., the largest research company in Japan. Several trap questions were included in the survey to identify respondents who did not seriously answer the questions. Those who did not correctly answer such trap questions were excluded from the survey company's sample in the collection process.

Entire Collapse of a Home (Item No. 1), Home Destruction (Item No. 2), Severe Damage to Property (Item No. 3), Severe Damage to Furniture (Item No. 4.), Death of Family or Friends (Item No. 5), Severe Injury (Item No. 6), Post-traumatic Stress Disorder, PTSD (Item No. 10), and Severe Health Problems (Item No. 11). We place the respondents with these items checked in Group 2. Following previous works, for Group 3, we exclude those who checked destruction of family property (Item No. 3) and severe damage to home furniture (Item No. 4.) from Group 2 to create a category with narrower coverage that includes the items that are more closely associated with PTSD ([75], [25]) that hinder driving ability. Consequently, we have 21,915 and 8,067 respondents in Groups 2 and 3, respectively, which are sufficient numbers of observations for us to conduct statistical analysis, as presented in Table 1.[4] The respondents belonging to each group are mutually exclusive, meaning that no respondent belongs to multiple groups. [5] The difference between Groups 2 and 3 is whether a person experiences partial damage to family property or damage to furniture, which are relatively minor compared to other types of items such as PTSD, the death of a family member, and severe injury.[6] Figure 3 clarifies for readers how we create the groups and which items denote membership in each group, with the proportion of each item after excluding those who had not experienced disaster damage and those who answered: "I don't know." The general pattern of this figure reveals that most damages would belong to Group 2, while Group 3 would cover a narrower range of damages.

[4]Note that the total numbers of observations are not equivalent to the 'analytical sample'; that is, we filter out some of the respondents according to certain criteria (i.e., we drop some observations if they have no awareness of FAVs). We further discuss this issue in Section 3.4.

[5]Not every person who has experienced a disaster loses driving ability, which would require a substantial level of physical and/or mental damage. Therefore, investigating disaster victims who lost their ability to drive requires dividing the observations into the disaster victims with and without a severe level of disaster experience.

[6]We do not address whether Group 2 or 3 has a more severe level of disaster damage. Instead, such differences are likely to be in the type of disaster damage. As mentioned in Section 1, for some people, the loss of driving ability may require a respondent to experience multiple instances of disaster damage, and this is likely to arise in Japan, where natural disasters are common. Therefore, we choose not to ask the respondents for the time and name of a specific disaster that caused their physical and mental damages. More attention should be devoted the which to which a respondent belongs.

Table 1: Criteria for Selecting Disaster Victims

No.	Item	Obs.	Portion(%)	Public	Disaster Victims	
				Group 1	**Group 2**	**Group 3**
1	Entire Home Collapse	1,474	1.47%	X	O	O
2	House Destruction	2,000	2.00%	X	O	O
3	Severe Damage to a Property	7,045	7.04%	X	O	X
4	Severe Damage to the Furniture	6,921	6.91%	X	O	X
5	Death of Family and Friends	1,137	1.14%	X	O	O
6	Severe Injury	1,019	1.02%	X	O	O
7	Evacuation	1,741	1.74%	X	X	X
8	Moving House	2,429	2.43%	X	X	X
9	Unemployment	1,369	1.37%	X	X	X
10	PTSD (Post-traumatic Stress Disorder)	879	0.88%	X	O	O
11	Severe Health Problems	836	0.84%	X	O	O
12	Others	3,591	3.59%	X	X	X
13	No experience.	69,647	70.92%	O	X	X
14	I don't know.	9,049	7.23%	X	X	X
	Total	100,810	100%	69,647	21,915	8,067
	Analytical Sample Total			57,105	7,853	4,433

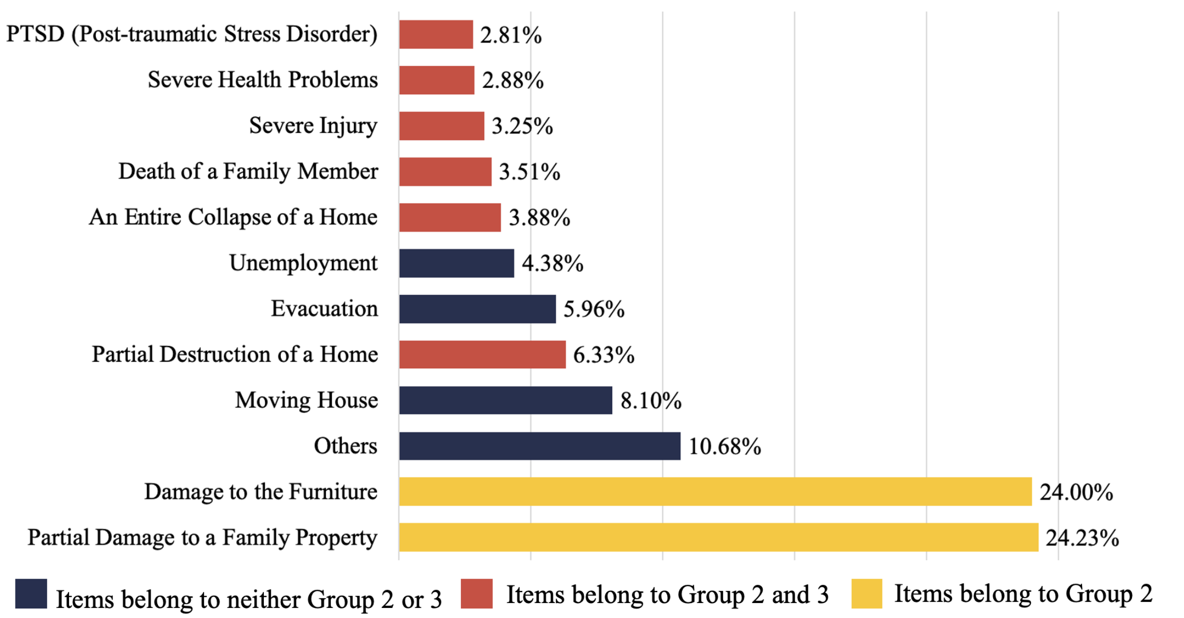

Figure 3: Distribution of Disaster Criteria Items

3.2 FAV-related Questions

For the questions related to FAV purchasing intention, respondents were asked the following question: "Do you want to add a completely self-driving option that allows you to move around when you purchase a car in the future?". The respondents were then offered the following response options: "(1) Purchase for sure, (2) Purchase under certain conditions, (3) Do not purchase, and (4) I don't know.". Given that FAVs had not yet been fully introduced into the market in 2017, we assume that people who show an affinity for FAVs can be potential consumers in the future.[7] Therefore, we include those who responded (1) or (2) in a group of 'potential consumers' because they show affinity toward using FAVs. On the other hand, people who responded (3) or(4) are reluctant to purchase FAVs, and we do not consider them potential consumers. Therefore, we code WTB equal to 1 if a respondent belongs to the potential consumer group and 0 otherwise. Using binary outcome variables for SEM is commonly used by previous works in the fields of transportation, as in [60], [59] and [31].

Therefore, our analysis allows us to identify which types of factors would shift consumers who belong to (3) or (4) to (1) or (2). Note that we make a clear distinction between "adding" a completely self-driving option and "purchasing" an FAV by asking "Do you want to add a completely self-driving option that allows you to move around when you purchase a car in the future?". Such a setting allows us to clearly distinguish between 'purchasing a car' and 'adding a self-driving option', which allows us to exclude potential deviations in the results due to the factors associated with purchasing a car, such as car price and vehicle attributes.[8]

Next, we also elicited the *perceived* FAV value (hereafter, FAV value) for FAVs, which refers to the *perceived* value of FAVs expressed in monetary term. Researches in the field of transportation conclude that the perceived value works as a predictor of purchase in-

[7] We would like to note that we do not believe that our data are outdated. Given that FAVs were not completely introduced in the market at the time and have yet to be introduced as of 2021, a substantial change in the results, for example, a change in sign or implications, is unlikely. Therefore, more attention should be given to the signs and relative comparisons of coefficient magnitudes of the latent constructs.

[8] We would also like to clarify that we do not employ all the information from the survey; that is, we do not treat survey answers on WTB as 'ordinal' but instead treat it as a categorical variable. For example, while it is possible to investigate the result of 'ordinal' responses on WTB by treating 1 not purchasing, 2 as not sure, 3 as considering purchasing and 4 as purchasing, an increase from 1 to 2 does not necessarily indicate the increase of the probability of a respondent purchasing an F/AV. Similarly, do not investigate the multinomial responses regarding WTB because we believe that each response is independent; therefore, investigating how the decision of 'not purchasing' based on another response, for example, 'not sure,' would not fit our research. Thus, we analyze binary responses because we are interested in whether a respondent would purchase an F/AV.

tentions ([40];[12]) and [10] and [20] suggests the role of perceived value in terms of autonomous vehicles and shuttles. Such analyses are capable because perceived values indicate influences on behavioral intentions, which this study is keen to look at through constructing latent variables. Thus, FAV values in this study work as an index showing the appreciation towards FAVs, rather than costs of automation which would show the negative relationship to purchase intentions. Therefore, it is quite natural that higher FAV value would be positively correlated to the higher chances of purchasing FAVs.

In this study, respondents were asked to freely write down their FAV value regardless of their purchasing decisions, leaving it as an open question. As we excluded the respondents unaware of FAVs, concerns regarding unrealistic answers – such as extremely high FAV values – are less likely to appear.

3.3 Sociodemographic Variables

To control for the respondents' sociodemographic characteristics, we also include sociodemographic variables: income, gender, age, number of family members, commuting time and commuting costs.[9] We also include a car ownership dummy (=1 if the respondent owns a car) and car type dummy (hybrid, plug-in hybrid) for two reasons. First, we want to increase the survey's internal validity; therefore, we would like to control for individuals who do not know the price and maintenance costs of cars. Thus, we included the 'car ownership' variable to control for those who do not own a car and are less likely to be aware of car prices. Second, along with car ownership, we also include car types (hybrid and plug-in hybrids (PHEVs)), because car prices differ according across these car types.[10]

While we only survey those who were aware of FAVs, it is possible that in 2017, the respondents were less familiar with FAVs than their counterparts in 2021 would be. Sorting out respondents who were not familiar with the FAV is necessary. Thus, we exclude

[9]For those who do not commute, the commuting time is treated as zero.

[10]We do not investigate other car types for two reasons: First, 90% of the Japanese car market consists of gasoline cars. Second, we do not observe substantial differences between gasoline cars and cars with other fuel types, such as diesel.

those who answered 'I don't know' to all of the questions related to FAVs (5,987 observations). Finally, we drop those who selected "don't know/don't want to answer" about their individual income (30,156 observations). As a result, we have 69,391 respondents in total.

Finally, we summarize our data in Table 2, which shows descriptive statistics of the key variables for full sample (the first column) and each group in the following columns. The average FAV values range from around 658,830 JPY to 868,030 JPY. As of October 2020, Tesla priced their full-driving capability (level 4 if all advertised features are delivered) as 871,000 JPY, in Tesla Model 3 (of vehicle price 4,590,000 JPY) [11] While our FAV value is lower than that of Tesla's, there is a fundamental difference between Tesla's case and the survey investigated in this study. Tesla is charging consumers with the promise that level-4 automation will be delivered in the future, and it is indeed based on the trust of Tesla, which is indeed a famous company. Compared to Tesla, respondents in our study would have uncertainty particularly in year 2017; therefore, it is clear that automation technology defined in this study should be appreciated lower. However, because our FAV values do not vary substantially compared to Tesla's market price, we would like to make a clear note that our FAV value can be used for the analysis.

The summary statistics in Table 2 indicate that the average WTB and FAV value of disaster victims (Groups 2 and 3) are higher than those of respondents who are not disaster victims (Group 1). Although the dummy variables are excluded from this table, we include the dummy variables for hybrid cars and PHEVs, a long commute dummy if commuting time exceeds 2 hours, and a short commute dummy if commuting time is less than an hour.

Interestingly, we find that both the WTB and FAV value increase as the disaster damage increases (moving from Group 1 to 2 and Group 1 to 3), indicating that disaster victims recognize the benefits of choosing FAVs. We do not observe substantial differences between WTB across groups; for example, the WTB of Groups 2 (0.533) and 3 (0.547) are

[11] We refer to the Tesla official website: Tesla, 2020. Autopilot. Retrieved 2020, from $https://www.tesla.com/en_ca/model3/design\#autopilot$.

11.7% and 14.47% higher than the Group 1 (0.477), respectively. However, we observe significant differences in FAV value between the full sample and Group 3, as the FAV value of Group 3 (86.803) is approximately 31.75% higher than the full Sample average (65.883). On the other hand, the FAV value of Group 2 does not show substantial differences from the full sample, as the FAV value of Group 2 is 5.23% (69.327) higher than the full sample average. Furthermore, while FAV value in Group 3 seems higher than in the full sample, the standard deviation is also higher (163.358 in Group 3 and 128.386 in Group 1), indicating the FAV value distribution within Group 3 is uneven. What factors motivate disaster victims to adopt and appreciate FAVs? Why are there more negligible differences across groups within WTB than within FAV value? Because there are fewer differences within sociodemographic variables (e.g., income, age, commuting time,), do psychometric attitudes influence WTB and FAV value? We answer these questions empirically by constructing latent variables and structural equation models explained in the following Subsections 3.4 and 4.1.)

3.4 Constructing Latent Variables

As mentioned in Subsection 3.3, we do not find significant differences in sociodemographic variables across groups. Therefore, we proceed to the empirical analysis of psychometric factors and construct latent variables. We identify the latent variables that can be related to WTB for FAVs based, whenever possible, on statements previously used and found to be effective in the literature(e.g., [51], [45]). Table 3 presents the names (acronyms) of our latent variables, items corresponding to them, and a list of references. In the following two paragraphs, we explain how we identify the latent constructs. The survey consists of questionnaires related to the following:

1. **Natural Disaster**: Whether a respondent has experienced a natural disaster that results in the loss of family, friends, and severe physical damage to the home and assets and whether the respondent has PTSD. It also captures whether and how fearful a respondent is, towards natural disaster.

Table 2: Descriptive Statistics of Analytical Sample

Variable	Mean	Std. Dev.	Min	Max
Full Samples (n=69,391)				
WTB (=1 if purchase FAVs)	0.488	0.500	0	1
FAV Values (10,000 JPY)	67.618	131.359	0	999
Female (=1 if female)	0.307	0.461	0	1
Annual Income (10,000 JPY)	511.958	420.924	100	3,500
Age	0.486	0.506	0	3.25
Commuting Time (Hours)	50.002	11.264	17	99
Household Members	2.785	1.315	1	10
Household Members: Preschoolers	0.132	0.432	0	5
Commuting Cost (1,000 JPY)	0.620	2.360	0	999
Car Ownership	0.802	0.398	0.00	1
Group 1 (n=57,105)				
WTB (=1 if purchase FAVs)	0.477	0.499	0	1
FAV Values (10,000 JPY)	65.883	128.386	0	999
Female (=1 if female)	0.315	0.465	0	1
Annual Income (10,000 JPY)	511.001	415.594	100	3,500
Age	49.747	11.170	17	99
Commuting Time (Hours)	0.487	0.505	0	3.25
Household Members	2.784	1.313	1	10
Household Members: Preschoolers	0.134	0.433	0	5
Commuting Cost (1,000 JPY)	0.614	2.309	0	99
Car Ownership	0.796	0.403	0	1
Group 2 (n=7,853)				
WTB (=1 if purchase FAVs)	0.533	0.499	0	1
FAV Values (10,000 JPY)	69.327	131.588	0	999
Female (=1 if female)	0.264	0.441	0	1
Annual Income (10,000 JPY)	514.326	422.616	100	3,500
Age	52.450	11.430	17	96
Commuting Time (Hours)	0.459	0.502	0	3.25
Household Members	2.815	1.300	1	10
Household Members: Preschoolers	0.117	0.415	0	5
Commuting Cost (1,000 JPY)	0.591	2.239	0	80
Car Ownership	0.849	0.358	0	1
Group 3 (n=4,433)				
WTB (=1 if purchase FAVs)	0.547	0.498	0	1
FAV Values (10,000 JPY)	86.803	165.358	0	999
Female (=1 if female)	0.285	0.452	0	1
Annual Income (10,000 JPY)	520.088	481.752	100	3,500
Age	48.958	11.614	17	99
Commuting Time (Hours)	0.515	0.521	0	3.25
Household Members	2.754	1.366	1	10
Household Members: Preschoolers	0.139	0.452	0	5
Commuting Cost (1,000 JPY)	0.736	3.097	0	80
Car Ownership	0.801	0.399	0	1

2. **Social Support**: The extent to which a respondent trusts the government, local authorities, family and friends during disasters.

3. **FAV-related questions**: Expected benefits of FAVs or merits, and whether the respondents fear FAVs due to potential accidents (Accidents).

4. **Environmental Concerns**:Importance of environmental protection (Nature), importance of reducing environmental pollution (Pollution).

Table 3 presents the list of questions and the previous works to which we referred to create survey questions according to the latent categories. For the (fear of) natural disaster (ND) and social support (SP) variables, respondents were asked to answer about their fear of natural disasters and beliefs in social support from diverse authorities on a scale from 1 to 5, where (1) indicates strongly disagree; (2) indicates disagree; (3) indicates neither agree or disagree; (4) indicates agree; and (5) indicates strongly agree. For example, if a respondent believes that his/her life would be in danger due to a large-scale natural disaster (Question No. 1 in the Natural Disaster Item), s/he would mark (5).

Next, we asked concerns regarding the environment in terms of importance as a policy. Based on previous studies, we classified the environmental policy topics into eight factors referring to the House of Councilors, The National Diet of Japan, (2015). We have 13 questions in total, and the topics cover air pollution, environmental conservation, water pollution, endangered species conservation (biodiversity), reuse and recycling, waste disposal, and CO_2 emissions with questions such as, "How important is the policy to you?" The scale of responses is as follows: (0) for no awareness/interest at all – meaning that the difference between those who answer (0) and others would be whether that person at least has an interest in a certain policy/issue – (1) for very insignificant; (2) for insignificant; (3) for neither important nor insignificant; (4) for important; and (5) for very important. According to the context of the questions, we divide the questions into pollution (EP), if a question is related to air pollution and waste management, and nature (EN) if a survey item is related to biodiversity and natural environment conservation.

Table 3: Latent Variables, Explanation and Works Referenced

Explanation	**Source**
Latents on Risk Perceptions	
Natural Disaster (ND) (Cronbach's $\alpha = 0.6961$)	[27], [23], [9], [11], [33], [50]
ND1. Do you think your life will be in danger due to a large-scale natural disaster?	
ND2. Do you think your property (household, household goods, automobiles, etc.) will be damaged by a large-scale natural disaster?	
ND3. Do you think a large-scale natural disaster will isolate you from your surroundings?	
ND4. Do you think you will need to evacuate from your home during a disaster to save your life?	
Social Support (SP) ($\alpha = 0.6579$)	[3], [5], [28], [39], [78], [83]
When faced with difficulties such as supplies, money, and housing in times of disaster, choose the one that best describes your thoughts.	
SP1. I expect physical/mental support from the government, local authorities and public institutions.	
SP2. I expect physical/mental support from family members and friends.	
SP3. I expect physical/mental support from local volunteers and members of local communities.	
Latents on FAVs	
Fear (FE) ($\alpha = 0.7345$)	[44], [34], [95], [49], [84], [43]
FE1. There is a possibility that children will be able to move it on their own.	
FE2. There is a possibility that the software will be hacked (cyber security).	
FE3. A malfunction may cause accidents.	
FE4. It is unclear who is responsible for an accident due to FAV technology.	
FE5. Traffic volume and congestion might increase because those without a license can drive.	
FE6. A malfunction may take me to the wrong destination.	
Merits (MR) ($\alpha = 0.5658$)	[96], [52], [87], [81], [41], [68]
MR1. People can drive without a license.	
MR2. Burdens on driving would be decreased.	
MR3. Children can move the vehicle without a guardian.	
MR4. Able to do other work while driving. (Multitask)	
MR5. Able to avoid responsibility for traffic accidents.	
Pollution (EP) ($\alpha = 0.9558$)	[92], [36], [36], [42], [74]
EP1. Recycling is important.	
EP2. Cycle utilization rate (the percentage of the total amount of reusable and recycled materials to be injected into society), is important for preventing pollution.	
EP3. I think water quality should be improved.	
EP4. Alleviating particulate matter (PM 2.5.) pollution is critical for our society.	
EP5. Resolving air pollution (particularly photochemical smog) is important.	
Nature (EN) ($\alpha = 0.9188$)	[67], [71], [80], [18]
EN1. Preserving endangered species is important	
EN2. Preserving living animals (overall) is important.	
EN3. The ratio of green area within 1,500 meters of a house is important.	
EN4. Green purchasing: When purchasing goods and services, I consider the environmental impact before purchasing.	

4 Empirical Strategy

In this section, we introduce our empirical strategy, then explain how we identify the latent variables in our empirical model.

4.1 Methods

We choose structural equation modeling (SEM) to assess the relationship between factors that are correlated with the WTB and FAV value. SEM allows us to examine the psychometric factors that are correlated with people's intentions regarding FAVs. SEM can handle a substantial number of endogenous and exogenous variables and can include latent variables in the model, and is useful to analyze the relationship between individual's intention and behavior. Thanks to these benefits, SEM has been employed in many research fields incorporating psychometric modeling, such as psychology, sociology, educational research, political science, and marketing research.

Moreover, SEM offers simultaneous estimations of latent variables and exogenous variables and allows for correlations between latents. If the latent and exogenous variables are estimated sequentially, for example, one can conduct factor analysis to construct the latents in the first step and proceed to the estimation of latent and exogenous variables in the choice modeling; while this strategy is simple, it does not guarantee unbiased estimators of the parameters involved and tends to underestimate standard errors (see, for example, [88], [54]). Finally, we use a multigroup SEM analysis to examine the differences between disaster victims and those without disaster experiences. In that sense, we follow the empirical strategies used in the previous works on FAV demand applying SEM ([16], [98], and [55]). We use STATA and a maximum-likelihood model to estimate the model (see [72] for a discussion of sequential versus simultaneous estimation).

Based on the findings from the literature mentioned in Sections 1 and 2, we choose six latent variables: Natural Disaster, Social Support, Nature, Pollution, Merit, and Accidents. Because these items focus on the psychometric intentions of the potential consumers, we choose SEM, which allows such analysis.

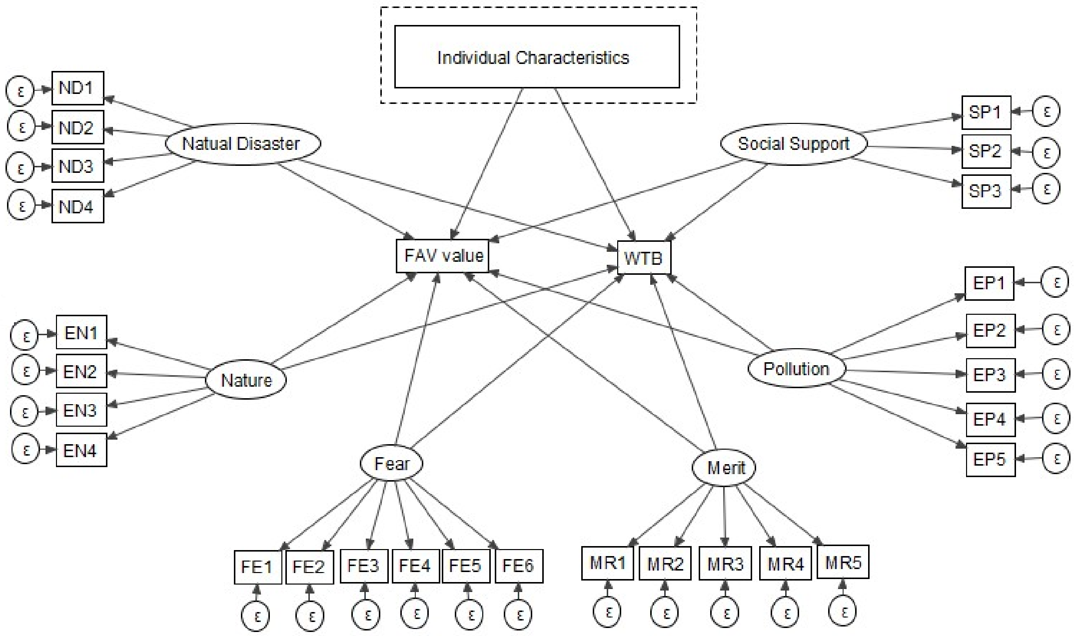

Figure 4: Graphically Explained our Brief Model Structures

4.2 Structural Equation Modeling

We used the latent constructs to create SEM models. We have four models in total. Figure 4 presents a brief structure of our SEM models. First, we investigate factors that are correlated with WTB (Model (1)) and FAV value (Model (2)). Second, we assume that FAV value would be correlated with WTB; therefore, we add such a relationship to Model (1) (Model (3)). Finally, we include Model (4), which assumes that all types of latents and other exogenous variables are correlated with both WTB and FAV value on top of Model (3). Our preferred main model is Model (4), and we use Models (1) to (3) to confirm our findings from Model (4). The diverse specifications employed in Models (1) to (3) allow us to confirm the robustness of the results of Model (4). In all models, we first estimate the demand for full sample, and included multigroup analysis that allows us to compare the estimated coefficients between Groups 1, 2 and 3. This setting also lets us to examine whether the differences in the estimated coefficients are statistically significant. In equation form, we simultaneously estimate the Model (4) as following:

$$\boldsymbol{w} = \boldsymbol{A}\boldsymbol{\eta} + \boldsymbol{B}\boldsymbol{x} + \boldsymbol{\epsilon}, \tag{1}$$

$$\boldsymbol{y} = \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\nu}, \tag{2}$$

where $\boldsymbol{w}(2 \times 1)$ is a vector of dependent variables of WTB/FAV value, $\boldsymbol{\eta}(6 \times 1)$ is a vector of 6 latent constructs, $\boldsymbol{x}(14 \times 1)$ is a set of 14 explanatory variables, $\boldsymbol{y}(27 \times 1)$ is a vector of 27 indicator variables for estimating latent variables, $\boldsymbol{A}(2 \times 6)$, $\boldsymbol{B}(2 \times 14)$, and $\boldsymbol{\Lambda}(27 \times 6)$ are matrices of unknown parameters to be estimated, and $\boldsymbol{\epsilon}(2 \times 1)$ and $\boldsymbol{\nu}(27 \times 1)$ are error terms. Equation (1) is called a structural equation, which describes the relationship between the latent and dependent variables, while equation (2) is a measurement equation, which is used for estimating the factor loading matrix $\boldsymbol{\Lambda}$ and predicting the score of latent variables $\boldsymbol{\eta}$. Specifically, equation (1) can also be written as follows:

$$\begin{bmatrix} WTB_i \\ Value_i \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} & \alpha_{15} & \alpha_{16} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} & \alpha_{25} & \alpha_{26} \end{bmatrix} \begin{bmatrix} SP_i \\ ND_i \\ FE_i \\ MR_i \\ EP_i \\ EN_i \end{bmatrix} + \begin{bmatrix} \beta_{10} & \beta_{11} & \boldsymbol{\beta'_{1x}} \\ \beta_{20} & 0 & \boldsymbol{\beta'_{2x}} \end{bmatrix} \begin{bmatrix} 1 \\ Value_i \\ \boldsymbol{x_i} \end{bmatrix} + \begin{bmatrix} \epsilon_{1i} \\ \epsilon_{2i} \end{bmatrix} \tag{3}$$

where i refers to each individual and α presents the correlation between each latent construct and WTB/FAV value, which is our main focus. Thus WTB_i and $Value_i$ refers to the WTB and FAV values of individual i, respectively. The parameters β_{10} and β_{20} are intercepts, β_{11} is the correlation between WTB and FAV value, and $\boldsymbol{\beta_{1x}}$ and $\boldsymbol{\beta_{2x}}$ show the correlation between WTB/FAV value and a set of 12 individual characteristics $\boldsymbol{x_i}$. To ensure better model fit, we assume that some of the error terms associated with indicator variables are correlated. Hypothesizing a correlation between these error terms can improve our model's ability to explain the data.

5 Results

In this section, we first explain our results in general in Subsection 5.1, then demonstrate the importance of social support in Subsection 5.2.

5.1 Main Result

In sum, our models provide suggestive evidence of the importance of social support in the WTB and FAV value. We report the results of Models (1) to (2) in Table 4 and Models (3) to (4) in Table 5 and 6. As mentioned in Section 4, the difference between Models (1) and (2) and Models (3) to (4) is whether we include the correlation between FAV value and WTB. We divide our results tables into three panels: Panel A displays the estimated coefficients of the latent variables, Panel B presents the estimation results of the socioeconomic variables, and Panel C shows the model fit. In Table 4, the first and fifth columns show the estimation results for full sample, the second and sixth column shows the results of Group 1, the third and seventh columns display the estimation results for Group 2, and the fourth and eighth columns display the estimation results for Group 3. For all models, we use standardized coefficients to permit comparison between the magnitudes of coefficients in all types of models, which is frequently used in quantitative studies to reflect the relative importance of explanatory variables within a model ([21]).

We do not observe substantial differences in model coefficients across Models (1) to (4). Thus, we choose to focus on Model (4) with the full specification when interpreting the results. The results of the measurement equation are shown in Table A3 in the Appendix. In this section, we briefly explain the results and further discuss on the implications in Subsection 6.1.

Notes on Interpretation. Before proceeding to interpreting the results, we want to clarify that people can have different combinations of latent variables. For instance, people can have high levels of both 'FE (Fear)' and 'MR (Merit)'. For example, concerns about accidents are negatively correlated with FAV value, and this does not indicate that a person with high levels of 'FE' does not appreciate the benefits of FAVs. Potential consumers would express appreciation for the benefits of FAVs given the results on the coefficients of 'MR.' Our result shows the changes in WTB and FAV value following one-standard-deviation increases in a latent variable, holding the other latent variables fixed. We focus on the comparison across the groups rather than explaining the results by groups. Overall, we find that the estimated coefficients of full samples are not substantially different from Group 1, and this is quite natural given that experiencing a severe level of disasters which are likely to be correlated to the loss of driving capability, is not common.

Social Support (SP) The results on social support are worthy of discussion. First, social support shows positive and statistically significant coefficients across all types of models and dependent variables, suggesting that social support is highly likely to encourage people to adopt/appreciate FAVs. Second, most of our results suggest that disaster victims show a substantially higher level of the social support coefficient than those who belong to Group 1 and full sample, indicating that disaster victims are more likely to regard social support as vital than those who do not experience disasters. Our results indeed provide suggestive evidence on the need to urge social support. We further discuss the policy-relevant implications of social support in Section 6.2. This observation is consistent with anecdotes from documents published by the Japanese government, indicating the support from local authorities and family is vital for achieving inclusive transportation.[12]

Natural Disaster (ND) The coefficients of ND are all positive and statistically significant, indicating that fear of natural disasters is likely to discourage people from choosing/appreciating FAVs. Note that ND is higher if people are *not* afraid of disasters. Thus, a positive coefficient implies that people would adapt/appreciate FAVs if they are not frightened of natural disasters. Note that the estimated coefficient of ND, in terms of FAV value, is slightly smaller in Group 2(0.038) and Group 3 (0.044) than in Group 1 (0.055)

[12] We refer to the Japanese Cabinet's Guideline entitled "Social Principles of Human-Centric AI" (2020).

and full sample (0.055). On the other hand, for WTB, the estimated coefficient of ND would be more significant for those who belong to Group 2 (0.074) and Group 3 (0.082) than to Group 1 (0.055) and entire samle (0.060). This result suggests that the effect of ND is more likely to prevent disaster victims from choosing FAVs (as expressed in WTB), while it does not prevent disaster victims from appreciating FAVs (as depicted by FAV value). Nonetheless, the differences between coefficients across groups were not substantial.

Fear (FE) and Merit (MR) As expected, merit would encourage and accidents would discourage people from choosing/appreciating FAVs. These results are reasonable in the sense that people who appreciate the benefits of using FAVs would have higher WTB and FAV value, and those who fear potential accidents would not be more likely to purchase FAVs or appreciate FAVs than those who do not fear FAVs. Similar to ND, we do not find substantial differences between groups and WTB/FAV value.

Environmental Concerns ((EP) and (EN)) EP (which stands for Pollution) shows insignificant coefficients in WTP, it displays a positive coefficient of 0.022 in Group 1's WTB, a negative coefficient of -0.047 in Group 2, and an insignificant coefficient in Group 3. On the other hand, EN (which stands for Nature) shows positive coefficients across groups, both in WTB and FAV value.

Socioeconomic Variables Regarding the remaining parameters, as expected and consistent with the previous works on FAV demand, socioeconomic attributes mostly exhibit statistically significant coefficients, implying that these characteristics also play a role in FAV demand. We also find some interesting results for the socioeconomic variables: 1) women and older respondents present high FAV value but lower WTB. 2) Car ownership presents a negative coefficient for FAV value and a positive coefficient for WTB. This result is explained by previous works ([1], [89], [79]), which report that drivers enjoy or are satisfied with the sense of driving themselves and thus may not be attracted by FAVs. This result indicates that there should be more policy-relevant efforts to encourage drivers to appreciate the benefits of FAVs. 3) (Plug-in) hybrid cars show positive coefficients, indicating that those who purchase such cars are likely to be attracted by FAVs, which is consistent with previous works ([6], [70]). Other socioeconomic variables, particularly those correlated with commuting behavior, were either insignificant or inconsistent across groups, indicating weak correlation between them and the WTB/FAV value for FAVs.

Model Fit According to the goodness-of-fit indices shown at the bottom of the table, in general, the models fit the data modestly well. The acceptable range of RMSEA is < 0.08, those of CFI and SRMR are < 0.90 and <0.05, respectively. ([65], [37]). In our model, the values of RMSEA, CFI and SRMR are generally within or near each variable's acceptable range.

WTB and FAV Value Throughout Models (3) and (4), we find positive correlations between WTB and FAV value of approximately 0.3, indicating the 'overall' trend that people with a high level of WTB are likely to have higher perceived FAV Value and vice versa.

The results above indicate the importance of social support as well as other latent variables. However, it is difficult to determine whether the differences across groups are statistically significant, which inspires us to test the group heterogeneity of the estimated coefficients in Subsection 5.2 below.

Table 4: Estimation Results of Models (1) and (2)

	Model (1) (WTB)				Model (2) (FAV value)			
	All	**Group 1**	**Group 2**	**Group 3**	**All**	**Group 1**	**Group 2**	**Group 3**
Panel A: Latent Variables								
SP	0.069***	0.095***	0.088***	0.152***	0.101***	0.060***	0.079***	0.126***
	(.004)	(.005)	(.014)	(.016)	(.004)	(.005)	(.014)	(.016)
ND	0.076***	0.055***	0.038***	0.044**	0.055***	0.071***	0.086***	0.095***
	(.004)	(.004)	(.014)	(.016)	(.004)	(.004)	(.013)	(.016)
FE	-0.082***	-0.077***	-0.103***	-0.113***	-0.083***	-0.077***	-0.102***	-0.106***
	(.008)	(.009)	(.024)	(.032)	(.008)	(.009)	(.024)	(.033)
MR	0.215***	0.142***	0.150***	0.146***	0.143***	0.217***	0.203***	0.231***
	(.008)	(.009)	(.025)	(.033)	(.008)	(.009)	(.025)	(.033)
EP	0.013	0.011	-0.027	-0.0388	0.006	0.026***	-0.048**	-0.052
	(.009)	(.009)	(.026)	(.035)	(.009)	(.009)	(.026)	(.035)
EN	0.061***	0.054***	0.073***	0.106**	0.061***	0.049***	0.112***	0.101**
	(.009)	(.009)	(.026)	(.034)	(.009)	(.009)	(.026)	(.034)
Panel B: Socioeconomic Variables								
Female	0.041***	0.064***	0.053***	0.033**	-0.059***	-0.039***	-0.034***	-0.048**
	(.004)	(.005)	(.013)	(.017)	(.004)	(.005)	(.013)	(.017)
ln(Income)	0.095***	0.109***	0.103***	0.110***	0.108***	0.100***	0.079***	0.065***
	(.004)	(.005)	(.013)	(.017)	(.004)	(.005)	(.013)	(.017)
ln(Age)	-0.116***	0.090***	0.093***	0.033*	0.086***	-0.006	-0.020	-0.059***
	(.004)	(.005)	(.013)	(.017)	(.004)	(.005)	(.013)	(.017)
Household Size	-0.011***	-0.020***	-0.0484***	-0.027	-0.024***	-0.008*	-0.018	-0.014
	(.004)	(.005)	(.012)	(.016)	(.004)	(.005)	(.012)	(.016)
Preschooler	0.016***	0.029***	0.0435***	0.0198	0.030***	0.018***	0.015	-0.003
	(.004)	(.005)	(.012)	(.016)	(.004)	(.005)	(.026)	(.016)
Car Ownership	-0.044***	-0.042***	-0.037***	-0.029*	-0.040***	0.045***	0.031***	0.027*
	(.004)	(.004)	(.012)	(.016)	(.004)	(.004)	(.012)	(.016)
Hybrid	0.061***	0.043***	0.042***	0.030**	0.043***	0.060***	0.059***	0.068***
	(.004)	(.004)	(.011)	(.015)	(.004)	(.004)	(.011)	(.015)
Plug-in Hybrid	0.014**	0.009**	0.002	-0.008	0.008**	0.014***	0.018	-0.009
	(.004)	(.004)	(.011)	(.015)	(.004)	(.004)	(.011)	(.015)
ln(Commute Time)	-0.024***	-0.030***	-0.028	-0.039*	-0.031***	0.025***	0.01	0.042
	(.007)	(.008)	(.022)	(.028)	(.007)	(.008)	(.012)	(.027)
Long Commute	-0.005	0.003	-0.009	0.02	0.004	-0.008*	0.004	0.008
	(.004)	(.004)	(.012)	(.016)	(.004)	(.004)	(.012)	(.016)
Short Commute	-0.025	-0.025***	-0.035**	-0.014	-0.024***	-0.003	-0.013	0.0328
	(.006)	(.006)	(.017)	(.023)	(.006)	(.006)	(.017)	(.022)
ln(Commute Cost)	0.027***	-0.005	0.006	0.032*	-0.001	0.025***	0.0182	0.051**
	(.007)	(.006)	(.015)	(.019)	(.005)	(.005)	(.015)	(.018)
Observations	69,391	57,105	7,853	4,433	69,391	57,105	7,853	4,433
Panel C: Model Fit								
RMSEA	0.045		0.044		0.045		0.044	
CFI	0.916		0.913		0.916		0.913	
SRMR	0.05		0.06		0.05		0.06	

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Estimation Results of Models (3)

	Model (3) (FAV value)				Model (3) (WTB)			
	All	**Group 1**	**Group 2**	**Group 3**	**All**	**Group 1**	**Group 2**	**Group 3**
FAV value					0.337***	0.337***	0.327***	0.338***
					(.003)	(.004)	(.010)	(.013)
Panel A: Latent Variables								
SP	0.101***	0.095***	0.088***	0.153***				
	(.004)	(.005)	(.013)	(.023)				
ND	0.055***	0.055***	0.038***	0.044***				
	(.004)	(.004)	(.014)	(.016)				
FE	-0.083***	-0.077***	-0.103***	-0.113***				
	(.008)	(.009)	(.024)	(.032)				
MR	0.143***	0.142***	0.150***	0.147*** *				
	(.008)	(.009)	(.025)	(.033)				
EP	0.006	0.011	-0.027	-0.039				
	(.009)	(.009)	(.026)	(.035)				
EN	0.061***	0.054***	0.073***	0.106**				
	(.009)	(.009)	(.026)	(.035)				
Panel B: Socioeconomic Variables								
Female	0.059***	0.064***	0.053***	0.033** *				
	(.004)	(.005)	(.013)	(.017)				
ln(Income)	0.108***	0.109***	0.103***	0.110***				
	(.004)	(.005)	(.013)	(.017)				
ln(Age)	0.086***	0.090***	0.093***	0.0328*				
	(.004)	(.005)	(.013)	(.017)				
Household Size	-0.240***	-0.020***	-0.048***	-0.027				
	(.004)	(.005)	(.012)	(.016)				
Preschooler	0.030***	0.029***	0.044***	0.0197				
	(.004)	(.005)	(.012)	(.016)				
Car Ownership	-0.040***	-0.042***	-0.037***	-0.029*				
	(.004)	(.004)	(.012)	(.016)				
Hybrid	0.043***	0.043***	0.042***	0.030*				
	(.004)	(.004)	(.011)	(.015)				
Plug-in Hybrid	0.008**	0.009**	0.002	-0.008				
	(.004)	(.004)	(.011)	(.015)				
ln(Commute Time)	-0.031***	-0.030***	-0.029	-0.0394				
	(.007)	(.008)	(.022)	(.028)				
Long Commute	0.004	0.003	-0.009	0.0205				
	(.004)	(.004)	(.012)	(.016)				
Short Commute	-0.026***	-0.025***	-0.035*	-0.014				
	(.006)	(.006)	(.017)	(.022)				
ln(Commute Cost)	-0.001	-0.005	0.006	0.0316				
	(.006)	(.006)	(.015)	(.019)				
Observations	69,105	57,105	7,853	4,433				
Panel C: Model Fit								
RMSEA	0.045				0.044			
CFI	0.913				0.913			
SRMR	0.06				0.06			

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 6: Estimation Results of Model (4)

	Model (4) (FAV value)				Model (4) (WTB))			
	All	**Group 1**	**Group 2**	**Group 3**	**All**	**Group 1**	**Group 2**	**Group 3**
FAV value					0.304***	0.305***	0.299***	0.290***
					(.004)	(.004)	(.011)	(.014)
Panel A: Latent Variables								
SP	0.101***	0.095***	0.088***	0.153***	0.039***	0.031***	0.053***	0.083***
	(.004)	(.005)	(.014)	(.023)	(.004)	(.005)	(.013)	(.016)
ND	0.055***	0.055***	0.038***	0.044***	0.060***	0.055***	0.074***	0.082***
	(.004)	(.004)	(.014)	(.016)	(.004)	(.004)	(.013)	(.015)
FE	-0.084***	-0.078***	-0.104***	-0.113***	-0.057***	-0.053***	-0.071***	-0.073**
	(.008)	(.009)	(.024)	(.032)	(.007)	(.008)	(.023)	(.031)
MR	0.144***	0.143***	0.151***	0.147***	0.172***	0.173***	0.158***	0.189***
	(.009)	(.009)	(.025)	(.033)	(.008)	(.009)	(.024)	(.032)
EP	0.011	0.011	-0.003	-0.039	0.011	0.022**	-0.047**	-0.041
	(.009)	(.009)	(.026)	(.035)	(.008)	(.009)	(.025)	(.033)
EN	0.061***	0.055***	0.074***	0.106**	0.055***	0.033***	0.090***	0.076**
	(.009)	(.009)	(.026)	(.035)	(.008)	(.009)	(.024)	(.033)
Panel B: Socioeconomic Variables								
Female	0.059***	0.064***	0.053***	0.033**	-0.059***	-0.059***	-0.049***	-0.058***
	(.004)	(.005)	(.013)	(.017)	(.004)	(.005)	(.012)	(.016)
ln(Income)	0.108***	0.109***	0.103***	0.110***	0.062***	0.067***	0.049***	0.033**
	(.004)	(.005)	(.013)	(.017)	(.004)	(.005)	(.012)	(.016)
ln(Age)	0.086***	0.090***	0.093***	0.0328*	-0.038***	-0.034***	-0.048***	-0.068***
	(.004)	(.005)	(.013)	(.017)	(.004)	(.005)	(.011)	(.016)
Household Size	-0.024***	-0.020***	-0.049***	-0.027	-0.009***	-0.002	-0.004	-0.006
	(.004)	(.005)	(.012)	(.016)	(.004)	(.004)	(.012)	(.016)
Preschooler	0.030***	0.029***	0.044***	0.0197	0.007**	0.009**	0.002	-0.006
	(.004)	(.005)	(.015)	(.016)	(.004)	(.004)	(.012)	(.015)
Car Ownership	-0.0402***	-0.043***	-0.037***	-0.029*	0.056***	0.058***	0.042***	0.0354**
	(.004)	(.004)	(.012)	(.016)	(.004)	(.004)	(.011)	(.015)
Hybrid	0.043***	0.043***	0.042***	0.030*	0.048***	0.047***	0.046***	0.059***
	(.004)	(.004)	(.011)	(.015)	(.004)	(.004)	(.011)	(.019)
Plug-in Hybrid	0.008**	0.009**	-0.002	-0.008	0.011**	0.011***	0.017	-0.006
	(.004)	(.004)	(.012)	(.015)	(.004)	(.004)	(.011)	(.015)
ln(Commute Time)	-0.031***	-0.030***	-0.028	-0.0394	0.033***	0.034***	0.018*	0.054**
	(.007)	(.008)	(.022)	(.028)	(.003)	(.007)	(.015)	(.026)
Long Commute	0.004	0.003	-0.001	0.0205	-0.006	-0.008**	0.004	0.002
	(.004)	(.004)	(.012)	(.016)	(.004)	(.004)	(.011)	(.016)
Short Commute	-0.026***	-0.025***	-0.035*	-0.014	0.005	0.005	-0.003	0.037*
	(.006)	(.006)	(.016)	(.022)	(.005)	(.006)	(.016)	(.021)
ln(Commute Cost)	-0.002	-0.005	0.006	0.0316	0.027***	0.026***	0.018	0.041***
	(.005)	(.006)	(.015)	(.019)	(.005)	(.005)	(.015)	(.018)
Observations	69,105	57,105	7,853	4,433	69,105	57,105	7,853	4,433
Panel C: Model Fit								
RMSEA	0.045				0.044			
CFI	0.916				0.91			
SRMR	0.05				0.06			

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

5.2 Supplementary Results

To determine whether the difference in estimated coefficients across groups is statistically significant, focusing on the latent variables, we test for invariance of the coefficients of each latent variable across groups. We conduct Wald tests to indicate whether we can reject the null hypothesis that the coefficients estimated in Model (4) do not differ across groups. Rejecting the null hypothesis implies the existence of group heterogeneity. Table 7 shows the results of the Wald tests and is divided into two panels: Panel A shows the Wald test results for FAV value, and Panel B presents the Wald test results for WTB. The first column provides the chi-squared statistics on the differences between Groups 1 and 2. Analogously, the second and third columns show the results for Groups 2 and 3 and Groups 1 and 3, respectively.

The results reveal that social support is the only latent with coefficients that differ substantially and significantly across groups. This trend is more substantial for FAV value because there are no statistically significant differences in coefficients across groups other than social support. We find additional evidence that social support has a significantly stronger correlation with WTB for Group 3 than Group 1 and 2. This is because comparing Group 1 to 3 shows higher and statistically significant coefficients (13.524 for FAV value, 9.803 for WTB) while comparing Group 1 to 2 does not yield statistically significant coefficients. This result allows us to interpret that people belonging to Group 3 recognize social support as a critical factor. Other than social support, the coefficients of environmental concerns (pollution and nature) differ significantly between Groups 1 and 2. The difference in the coefficients of ND and EP between Groups 1 and 3 are also significant, but the significance is relatively weak.

Finally, concluding on the importance of social support requires us to check the correlations between social support and other latent constructs. Suppose that social support is not highly correlated with other latents. In that case, we could conclude that social support is a unique and independent factor that is vital for inspiring disaster victims to choose FAVs. Table 8 shows the correlation matrix among the predicted scores of the latent variables. We do not find any latents that are closely correlated with social support.

Other than social support, the correlation between pollution (EP) and nature (EN) is the highest among the six latent constructs (0.889), followed by Fear (FE) and Merit (MR), which shows a correlation of 0.821. This result implies that those with a high level of EP (FE) have higher EN (MR), which is reasonable.

Table 7: Difference in Coefficients across Groups

	Group 1 vs. 2	**Group 2 vs. 3**	**Group 1 vs. 3**
Panel A: FAV value			
SP	0.519	12.756***	13.524***
ND	1.629	0.286	0.228
FE	0.839	0.293	1.383
MR	0.013	0.096	0.102
EP	0.261	0.794	1.819
EN	0.383	0.946	2.393
Panel B: WTB			
SP	2.515	2.035	9.803***
ND	2.17	0.15	3.025*
FE	0.552	0.012	0.375
MR	0.329	0.756	0.189
EP	7.099***	0.015	3.382*
EN	4.886**	0.114	1.585

Note: Each value shows the chi-squared statistic with significance obtained from the Wald test.* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 8: Correlation between Predicted Scores of Latent Variables

	SP	ND	FE	MR	EP	EN
SP	1					
ND	0.049	1				
FE	-0.018	0.150	1			
MR	0.016	0.076	0.821	1		
EP	0.107	0.284	0.284	0.286	1	
EN	0.133	0.095	0.204	0.189	0.889	1

6 Discussion and Policy Implications

Our results presented in the previous sections demonstrate the importance of social support in making FAVs inclusive. In this section, we first discuss our results in general in Subsection 6.1, then illuminate the importance of social supports in Subsection 6.2.

6.1 Result Implications

We answer whether FAVs can be an inclusive transport mode by examining how FAV adoption and appreciation are shaped, focusing on disaster victims. To do so, we consider individual-level demographic characteristics and individual-level psychometric attributes of social supports, fear of a natural disaster, natural environment conservation, pollution reductions, accident concerns, and merits. By including such characteristics, this study enables policymakers to move beyond simply observing the growth of FAV adoption patterns to actively directing the adoption path and making it inclusive. Our results inspire the design of effective policy instruments and information campaigns that appeal to disaster victims. Therefore, our findings provide clear, practical contributions.

This study discovers that social support is crucial for achieving inclusive transportation in the context of FAVs: Social support critically encourages disaster victims to choose and appreciate FAVs. This finding is consistent with previous works showing that family encouragement is a suitable stimulus for socially vulnerable people to accept new technology ([35]). The significance of the group heterogeneity coefficient provides further support for our findings. Our result suggests that social support is the only latent factor that exhibits statistically significant group heterogeneity coefficients in both WTB and FAV value.

Second, while previous works reveal that a higher level of environmental concern motivates FAV adoption, interestingly, we find group heterogeneity in environmental concerns where the implications differ according to the type of environmental concern (natural environmental preservation and pollution reduction). Our result emphasizes the importance of separately identifying environmental awareness according to context.

One possible explanation for this difference relies on the characteristics of disaster victims. Recall from the literature that disaster victims are interested in whether choosing FAVs would reduce or prevent damage from natural disasters. Activities related to pollution reduction are not directly connected to disaster damage mitigation (and are therefore less attractive to disaster victims). However, pollution reduction activities might be associated with direct environmental damage alleviation (and thus be attractive for the people without disaster experiences). Future studies can explore the detailed reasons for the differences and group heterogeneity.

Third, our result shows that the concerns about possible accidents and merits are significant predictors of FAV adoption. However, we do not find group heterogeneity in their estimated coefficients. Nonetheless, such a finding does not indicate that the accidents and merits are not interconnected to disaster victims' FAV adoption but shows that disaster experience does not shift the underlying importance of both factors.

6.2 Social Support and Policy Implications

This study extends the work of [30], [48] that incorporates the effect of social interaction into the choice model. Specifically, it contributes by 1) examining disaster victims, 2) focusing on WTB and FAV value, 3) including other latent variables associated with disasters, accidents, merits, and environmental concerns, and 4) scrutinizing the group heterogeneity of social support with respect to disaster experience. Through such additional contributions, we confirm the significance of social support.

Our findings provide suggestive policy implications for policymakers worldwide who are keen to make FAVs inclusive. On the one hand, the interaction between WTB and social support suggests that encouraging social support through the government and local authorities establishing and publishing guidelines on FAVs would motivate widespread adoption of FAVs by disaster victims. On the other hand, an increase in social support can motivate disaster victims to perceive FAVs as beneficial for them. Thus, extending the findings of previous works highlighting the importance of social support in driving/vehicle choices ([82], [26]), this study provides additional implications by reconciling the findings from social support to fear of natural disasters, which is likely to hinder FAV adoptions/appreciations, with a statistically significant group heterogeneity coefficient for WTB.

Providing a governmental (or local institutional) guidelines on the prior knowledge of FAVs would significantly alleviate the negative influence of concerns associated with the locus of losing control. Most of the obstacles that hinder disaster victims from choosing FAVs derive from the fear of 'losing control,' particularly in times of accidents, which thus renders them more fearful than others of new technology ([7], [63]). In that sense, our study reaffirms the findings of the past studies that have noted the impact of prior knowledge on attitudes toward new kinds of vehicles (e.g., electric cars) and on intentions to use them ([73]). Such a finding would apply to both disaster victims and people without disaster experiences.

Family and peer support can encourage disaster victims to adapt to new technologies or return to driving, according to previous medical studies on traumatic symptoms ([62]). Rather than hastily pushing disaster victims to adopt and appreciate FAVs, gradually letting them adopt the usage of FAVs through repeated short-term travel or simulation-based training with the support of family and friends would be desirable. Such a conclusion also implies that social support can work as a stimulus for disaster victims to overcome the fear of disasters, which hinders them from choosing FAVs.

7 Concluding Remarks

Achieving inclusive transportation requires accommodating socially vulnerable people who are not able to drive unassisted. Focusing on FAVs and disaster victims, our results indicate that social support is pivotal in motivating disaster victims to adopt and appreciate FAVs. We find additional evidence on the relationship between other psychometric factors and socioeconomic factors with FAV demand.

While our study offers several advantages over previous studies, it also has several important limitations and presents avenues for future work. First, our research adopts SEM, which contains a possible concern of reverse causality. For example, a disaster victim who had always wished to purchase an FAV might overestimate the merits of FAVs and underestimate the risks of accidents. Such reverse causality might be addressed by using an instrumental variable (IV) approach. For example, IVs that control for the traits of early adopters or those with fixed demands can be employed. Unfortunately, we lack the variables necessary to differentiate them.

Although we use data from Japan because doing so allows us to secure a sufficient number of disaster victims for the sample, we believe that our empirical framework can be extended to a global context, as many countries are keen on achieving inclusive transportation and encourage people to choose FAVs. Ultimately, by illuminating the importance of social support for FAV choices, our study suggests the importance of providing prior knowledge through institutional guidelines and enticing disaster victims to choose FAVs by increasing support from family and friends. Doing so could allow FAVs to be inclusive in the future.

Contributions

Sunbin YOO: Conceptualization, Methodology, Formal analysis, Writing (Original Draft); Junya KUMAGAI: Conceptualization, Methodology, Writing (Review and Editing); Yuta KAWABATA: Writing (Review and Editing); Shunsuke MANAGI: Resources and Supervision.

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Appendix

Table A1 presents the distribution of the socioeconomic variables in our sample and government statistics. Table A2 shows the average score (when we ask respondents to respond on 1-5 point scales) and proportion of respondents' evaluations of benefits and concerns regarding FAVs (for multiple choice questions). We calculate the proportions as follows: The number of people who choose the option/sample size (N=100,803).

Table A1: Socioeconomic Distribution of the Respondents and the Japanese Population

		Sample (%) (n =100,803)	**Government Statistics (%)**
Gender	Female	41	51.3
	Male	59	48.7
Education level	Junior high school or less	2.1	9.5
	High school	26.9	42.3
	Some college	22.6	15.6
	Bachelor / Master / Doctor	45.9	23.9
	Other	1.9	8.6
Age	18–19	0.2	2.3
	20–29	5.4	11.7
	30–39	18.1	13.3
	40–49	31.9	17.2
	50–64	25.8	22.1
	Over 65	10.7	33.4
Household income	<2 million JPY	7.8	18.3
	2–3 million JPY	8.9	17.2
	3–4 million JPY	11.9	15.3
	4–5 million JPY	12.3	12.2
	5–6 million JPY	11.9	9
	6–7 million JPY	9.6	6.9
	7–8 million JPY	9.1	5.8
	8–9 million JPY	6.9	4.1
	9–10 million JPY	6.7	3.4
	10–15 million JPY	10.5	6
	15–20 million JPY	2.7	1.1
	$\geq$ 20 million JPY	1.7	0.7
	Don't know / don't want to answer	-	–
Region	Hokkaido	4.6	4.2
	Tohoku	5.9	6.9
	Kanto	38.2	34.4
	Chubu	16.6	16.8
	Kinki	20.1	17.7
	Chugoku	5.1	5.8
	Shikoku	2.5	2.9
	Kyushu/Okinawa	7.1	11.3
Household size	1	15.6	34.5
	2	30.1	27.9
	3	23.6	17.6
	4 and above	30.1	20

Sources: MIC (2017, 2019a, 2019b)

Table A3 shows the results of the measurement equation, which describes the effects of the latent constructs on each of indicator variables. Standardized coefficients are shown, and all coefficients are positive and statistically significant at 0.1%. We only

Table A2: Proportion and Mean Value of Respondents' Evaluations for Each Latent Construct.

Latent Category	All	Group 1	Group 2	Group 3
Latent Category 1: "Natural Disaster", 1-5 Point Scale		Mean Value		
ND1. Do you think your life will be in danger due to a large-scale natural disaster?	2.31	2.32	2.3	2.13
ND2. Do you think your property (household, household goods, automobiles, etc.) will be damaged by a large-scale natural disaster?	2.11	2.13	2.01	2
ND3. Do you think a large-scale natural disaster will isolate you from your surroundings?	2.51	2.53	2.53	2.34
ND4. Do you think you will need to evacuate from your home during a disaster to save your life?	2.73	2.74	2.72	2.64
Latent Category 2: "Social Support", 1-5 Point Scale		Mean Value		
SP1. I expect physical/mental support from the government, local authorities and public institutions.	2.36	2.35	2.41	2.49
SP2. I expect physical/mental support from family members and friends.	2.47	2.45	2.54	2.56
SP3. I expect physical/mental support from local volunteers and members of local communities.	2.37	2.36	2.41	2.46
Latent Category 3: "Merit", Multiple Choice		Evaluation (%)		
MR1. People can drive without a license.	12.31%	12.08%	13.74%	12.75%
MR2. Burdens on driving would be decreased.	36.43%	36.12%	40.85%	32.94%
MR3. Children can move the vehicle without a guardian.	3.94%	3.84%	4.68%	3.98%
MR4. Able to do other work while driving. (Multitask)	27.96%	27.63%	32.08%	24.91%
MR5. Able to avoid responsibility for traffic accidents.	12.01%	11.84%	13.00%	12.50%
Latent Category 4: "Fear", Multiple Choice		Evaluation (%)		
FE1. There is a possibility that children will be able to move vehicles on their own.	33.74%	36.02%	39.09%	35.52%
FE2. There is a possibility that the software is hacked. (Cyber security)	65.13%	33.74%	37.85%	31.26%
FE3. A malfunction may cause accidents.	80.23%	53.04%	58.76%	45.29%
FE4. It is unclear who is responsible for an accident due to FAV technology.	76.63%	48.37%	53.04%	43.48%
FE5. Traffic volume and congestion might increase because those without a license can drive.	52.98%	25.01%	26.91%	24.11%
FE6. A malfunction may lead me to the wrong destination.	51.20%	23.82%	28.10%	23.13%
Latent Category 5: "Pollution", 1-5 Point Scale		Mean Value		
EP1. Recycling is important.	3.43	3.41	3.58	3.43
EP2. Cycle utilization rate, the percentage of the total amount of reusable and recycled materials to be injected into society, is important for preventing pollution.	3.34	3.31	3.48	3.35
EP3. I think water quality should be improved.	3.37	3.35	3.54	3.37
EP4. Alleviating particulate matter (PM) 2.5. pollution is critical for our society.	3.48	3.46	3.65	3.47
EP5. Resolving air pollution (particularly, photochemical smog) is important.	3.45	3.43	3.62	3.44
Latent Category 6: "Nature", 1-5 Point Scale		Mean Value		
EN1. Preserving endangered species is important.	2.94	2.92	3.04	3.01
EN2. Preserving living animals (overall) is important.	2.83	2.81	2.94	2.93
EN3. The ratio of green area within 1,500 meters of a house is important.	3.08	3.06	3.21	3.13
EN4. Green purchasing: When purchasing goods and services, I consider the environmental impact before purchasing.	3.02	3	3.15	3.09

present the measurement equation results of Model (4) because the coefficient values are almost unchanged across the five specifications including the robustness check. The results of the other specifications are available upon request. Note the need for caution when explaining the results in Tables 4, 5 and 6. While we observe generally positive correlation between the latent variables and indicator variables, we find exceptional evidence for ND. Such a difference suggests that if the respondent has high score on ND, s/he is not afraid of the risk of natural disasters. Therefore, a low score on ND can be regarded a respondent being afraid of natural disasters. On the other hand, for example, a high score on SP implies that the respondent is likely to expect social support.

Table A3: Coefficients of Measurement Equations

	Group 1	Group 2	Group 3
SP			
SP1	0.501	0.485	0.452
	(0.004)	(0.005)	(0.006)
SP2	0.574	0.563	0.560
	(0.004)	(0.005)	(0.006)
SP3	0.861	0.839	0.810
	(0.005)	(0.006)	(0.008)
ND			
ND1	-0.904	-0.871	-0.863
	(0.002)	(0.004)	(0.005)
ND2	-0.806	-0.766	-0.780
	(0.002)	(0.004)	(0.005)
ND3	-0.672	-0.643	-0.645
	(0.003)	(0.004)	(0.005)
ND4	0.131	0.129	0.113
	(0.004)	(0.004)	(0.004)
FE			
FE1	0.524	0.513	0.518
	(0.003)	(0.005)	(0.005)
FE2	0.596	0.583	0.615
	(0.003)	(0.005)	(0.006)
FE3	0.610	0.611	0.625
	(0.003)	(0.005)	(0.006)
FE4	0.588	0.585	0.603
	(0.003)	(0.005)	(0.006)
FE5	0.511	0.502	0.525
	(0.003)	(0.005)	(0.006)
FE6	0.535	0.514	0.546
	(0.003)	(0.005)	(0.006)
MR			
MR1	0.413	0.395	0.405
	(0.004)	(0.005)	(0.006)
MR2	0.602	0.589	0.627
	(0.004)	(0.005)	(0.006)
MR3	0.371	0.345	0.370
	(0.005)	(0.005)	(0.006)
MR4	0.506	0.486	0.523
	(0.004)	(0.005)	(0.006)
MR5	0.421	0.404	0.410
	(0.004)	(0.005)	(0.006)
EP			
EP1	0.860	0.866	0.854
	(0.001)	(0.003)	(0.004)
EP2	0.849	0.840	0.838
	(0.001)	(0.002)	(0.003)
EP3	0.899	0.894	0.897
	(0.001)	(0.002)	(0.002)
EP4	0.937	0.938	0.923
	(0.001)	(0.001)	(0.002)
EP5	0.946	0.944	0.931
	(0.001)	(0.001)	(0.002)
EN			
EN1	0.884	0.877	0.877
	(0.001)	(0.002)	(0.003)
EN2	0.874	0.864	0.855
	(0.001)	(0.002)	(0.003)
EN3	0.868	0.859	0.852
	(0.001)	(0.002)	(0.003)
EN4	0.828	0.820	0.817
	(0.001)	(0.003)	(0.004)

Note: All coefficients are statistically significant at the 0.1% level.

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Contributions

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