

## PSYCHOSOCIAL FACTORS ASSOCIATED WITH INTENDED USE OF AUTOMATED VEHICLES: A LATENT-CLASS AND LATENT-VARIABLE ANALYSIS

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### MOTIVATION

Automated Vehicles (AVs) present tremendous opportunities for humans, and have drawn the attention of policymakers, manufacturers, consumers and non-governmental organizations. AVs have the potential to revolutionize the way we travel because of their ability to move without human drivers (The Gartner, 2019). Predictions in the personal vehicle ownership space estimate 30% to 50% of the vehicles to have Level 4 automation in 2040 to 2050 (Litman, 2015), while logistics sector is likely to leverage full automation in the next decade (Chottani *et al.*, 2018). Such estimated approval will bring huge challenges not only for the suppliers (development of such complex technology) but also for the customers and particularly for policymakers. Impacts of AV are expected to be observed in various stages, such as: short-term changes in mode share and vehicle miles travelled (VMT); medium-term changes in vehicle ownership level and residential location; and long term reduction in number of crashes, cost of congestion, energy consumption and pollution, and changes in the land-use pattern. AVs are also predicted to have huge economic impacts (Shanker *et al.*, 2013). These potential impacts influence the models of vehicle ownership, patterns of land use and may create new markets and economic opportunities. However, questions about the behavioural changes induced by AVs in a fully automated era are also extremely relevant. Strategic policy implications studies in the domain of integrated transport and land use planning depend on robust estimates of population sensitivities with respect to travel- and lifestyle-related variables (e.g. Bhat and Guo, 2007; Pinjari *et al.*, 2007; Schwanen and Mokhtarian, 2005). The lifestyle-based approach to travel behaviour analysis recognises complex interdependencies between travel behaviour, residential location and lifestyle orientations (Van Acker *et al.*, 2010). It is understood that travel behaviour and residential location are co-determined by lifestyle goals pertaining to travel, neighbourhood and housing (Bhat and Guo, 2007; Pinjari *et al.*, 2007; Schwanen and Mokhtarian, 2005). As a consequence, a household's location choice involves trade-offs between a variety of travel- and lifestyle-related variables (Guo *et al.*, 2018; Rouwendal and Meijer, 2001; Walker and Li, 2006); in particular, balancing housing expenses against household members' travel times and costs to reach frequently-visited destinations such as the workplace. With the advent of AVs, some travellers' generalized cost of car travel may decrease. From this supposition, the question arises as to how we can quantify the effect of residential location choices in preferences towards adoption and use of AVs and in return, to what extent the use of AVs may affect residential location preferences. A growing body of literature investigates preferences for different aspects of autonomous driving

with the help of discrete choice experiments (see Gkartzonikas and Gkritza, 2019, for a comprehensive review). The studies within this body of literature consider short- and long-term decision contexts, but interdependencies between preferences for residential location and travel behaviour have only recently made it to be the topic of investigation (Daziano *et al.*, 2017; Shabanpour *et al.*, 2018; Haboucha *et al.*, 2017; Krueger *et al.*, 2016; Winter *et al.*, 2017; Kolarova *et al.*, 2017). We plan to model these two inter-dependent behavioural elements. Both residential location and AV acceptance have been of keen interest to behavioural researchers, but only few studies have modelled them in view of the fact that the two decisions are inter-correlated. Conjecturing that the influences on these choices will differ by attitudes toward AVs and other subjects, we will investigate the existence of taste heterogeneity in the sample through latent segmentation approaches.

### **ADVANTAGES AND RISKS ASSOCIATED WITH AUTOMATED VEHICLES**

AVs are expected to reduce greenhouse gas (GHG) emissions under efficient road pricing (Litman, 2019), to which the transportation sector is a prime contributor. AVs also have the potential to reduce transportation cost (Bagloee *et al.*, 2016), reduce accidents by 90 percent due to minimal human involvement (Kyriakidis *et al.*, 2015), enhanced critical mobility for elderly and disabled people (Litman, 2019), increased fuel efficiency (Kyriakidis *et al.*, 2015; Li *et al.* 2018), reduce physical and mental stress for drivers (Buckley *et al.*, 2018), reduce traffic congestion (Fraedrich *et al.*, 2018; Li *et al.*, 2018), increase the value of travel time (Greenwald and Kornhauser 2019; Litman, 2017; Chen *et al.* 2017; Mersky and Samaras, 2016; Economist 2018; Keen, 2013), reduce vehicle ownership (Bagloee *et al.*, 2016), and ease-of-parking (Nourinejad *et al.*, 2018). Yet they also pose risks and challenges related to safety, cybersecurity, privacy and liability, that technology has not yet been able to overcome. For instance, these types of vehicles are not entirely able to navigate in poor weather conditions where rain or snow may interfere with the proper functioning of vehicle sensors or obscure road markings; instead they must rely on capable drivers to take control (Kovacs, 2016). Further evidence has emerged in the past few years that demonstrates the propensity of drivers to modify their driving habits in unacceptable or more dangerous ways and increase their risk of collision when using new technology by speeding, not paying attention to the driving task, or in other ways circumventing the safety benefits of technology (Rudin-Brown *et al.*, 2011; Robertson *et al.*, 2012). Such arguments foster a sense of uncertainty in the expected benefits of AVs and, more generally speaking, point to the presence of obstacles or potential barriers that need to be addressed to accelerate AV adoption (Gkartzonikas and Gkritza 2019; Bansal and Kockelman, 2017; Becker and Axhausen, 2017). Managing the risks and maximizing the benefits of AVs requires carefully designed policies that are based on objective research related to human acceptance of new technologies and driver's knowledge, attitudes and perceptions towards AVs.

From a policy perspective, there are uncertainties related to the societal constraints and conditions for AV deployment and the contribution of such deployments towards general transportation goals. One such constraint that demands immediate attention of the researchers is the users' perception of safety and other potential benefits that AVs may provide. Some studies seek to improve this technology by addressing all the risks associated with it, for example, the detection of other vehicles and road users (Häne *et al.*, 2015; Litman, 2015; Levinson *et al.*, 2011). While others, (Merat and Lee, 2012) investigate interactions between human-drivers and automated vehicles and conclude that automation cannot substitute flawlessly for a human driver, nor the driver can safely accommodate the limitations of automation. Despite the growing body of travel behaviour literature on individual's preferences toward automation (Bansal *et al.*, 2016) and AVs (Krueger *et al.*, 2016; Haboucha *et al.*, 2017), there are limited studies that simultaneously investigate safety perception determinants and intention to adopt AVs (Becker and Axhausen, 2017). From a transportation planning perspective, the apparent mismatch between the automotive industry pace and consumers' perspectives leads to highly uncertain adoption scenarios. Hence, to build AV adoption forecasts, it is urgent to understand the relationship between individuals' perceptions and the resulting AV technology acceptance. In doing so, we must address the physical (e.g., infrastructure development) and psychological barriers (e.g., public perception) to the large-scale adoption of

AVs (Bagloee *et al.*, 2016). There is a pressing need to understand such barriers to expedite the future adoption of AVs (Fagnant & Kockelman, 2015; Gkartzonikas and Gkritza 2019; Haboucha *et al.*, 2017; Sparrow and Howard 2017). The great challenge for the researchers today is to understand the perception of consumers towards the adoption of driverless cars in order to inform policymakers in a time bound manner to help them plan for smooth implementation of infrastructure for driverless vehicles.

## PSYCHOLOGICAL THEORIES EXPLAINING ACCEPTANCE OF NEW TECHNOLOGIES

In order to understand the entire process from the knowledge of the existence of Automated Vehicles to their integration in the daily practices of individuals, three major theoretical approaches each address a phase of the process: social acceptability, practical acceptability and acceptance. They correspond, respectively, at a particular time when the individual is confronted with technology: before use, from the first use and after long-term use. We here focus on the social acceptability. Models and theories of social acceptability incorporate dimensions which may or may not give rise to intentions to use a technology by potential users. These intentions may, in turn, lead to the actual use of technology. According to Terrade *et al.* (2009, p. 384) "the consideration of acceptability refers to the examination of conditions that make this product or service acceptable (or not) to the user prior to its use real and effective". In this sense, social acceptability would be the first step in the process of accepting Automated Vehicles (AV). One of the oldest theories we can identify that can help us to inform about the adoption of the AVs is the model for the Diffusion of Innovation (Rogers, 1983). From this work, we distinguish two families of models to explain social acceptability: 1) socio-psychological models explaining the intention and 2) models which explain acceptability in a socio-domestic context.

1. Socio-psychological models: Theory of Reasoned Action (TRA, Fishbein and Ajzen, 1975) involves attitudinal dimensions (the degree to which engagement in behaviour is positively valued) and subjective norms (social pressure from important others to engage in a particular behaviour and relates them to the intended behaviour that precedes actual behaviour. Ajzen (1991) takes TRA model and develops it further as the basis for the Theory of Planned Behaviour (TPB), with an additional variable, the perceived behavioural control (PBC), which states that people are more likely to perform a behaviour when they perceive it as easy to perform.
2. Socio-domestic models: Technology Acceptability Model (TAM, Davis 1989) is based on the TRA. Unlike the other authors, Davis focuses on the perception of uses. It is based on the principle that perceptions that users have of the usefulness and usability of a technology, determine intentions that influence their usage behaviours. Although the TAM is derived from the TRA, it does not include the social dimension. In this theory, external variables influence the perception of the facility of use and the perception of the usefulness of the technology, which, in turn, impacts the attitudes toward Automated Vehicles.

For latest work in the application of psychometrics to understand the acceptance of automation in driving, the readers are referred to recent studies (Zhang T., *et al.* 2019a; Zhang T. *et al.*, 2019b; Montoro L. *et al.*, 2019; Liu P. *et al.*, 2019; Hudson J. *et al.*, 2019; Ge Y. *et al.*, 2019; Buckley L. *et al.*, 2018; Moták L. *et al.*, 2017; Payre W. *et al.*, 2014).

## THE CURRENT STUDY

The current paper builds on previous literature and develops a multivariate model to investigate the determinants of individuals' acceptance of AV technology. The analysis is based on data from the American Trends Panel (ATP) data. The individual was asked about their willingness to ride in an AV and based on their response (yes/no), they were asked to choose one of the given reasons. The respondent could choose between multiple alternatives, which formed the categories for the willingness-and-reason to ride (or not) an AV as a nominal dependent variable. In addition to socio-demographic variables, underlying latent psychological constructs representing Attitudes Towards Use, Perception of Safety, and Perceived Usefulness are used to capture individual taste heterogeneity and create classes of individuals with similar behaviour and response to AV acceptance. Within the endogenously formed latent classes, the study develops a model of AV acceptance for

an individual as a function of unobserved lifestyle stochastic latent constructs of Response to Innovation and Automation Acceptance, in addition to the land-use and built environment attributed related to residential location choice. The framework utilizes an endogenous latent-class segmentation methodology as given by Bhat (1997), to account for group taste heterogeneity based on the assumption that groups of individuals with contrasting attitudes towards use, perception of safety, and perceived usefulness behaviours may differ in the way they evaluate possible benefits of autonomous technologies to inform their decision of future AV acceptance. In the methodology, any number of segment-specific choice models can be estimated, and the number of segments can be decided using the best AIC or BIC values. The individuals are assigned to these segments in a probabilistic fashion incorporating their propensity values for latent constructs and socio-demographic values. Within each of these segments, a specification is developed to study the effect of response to innovation, automation acceptance and attributes of land-use and built-environment to understand the individuals' AV acceptance. The model results are used to evaluate possible changes in AV acceptance rates as a function of the confidence about this technology as perceived by different segments of the population. We also identify how each of the latent-class segments maps to acceptance rates.

## **METHODOLOGY**

### Group heterogeneity: Latent segments based on lifestyle

The modelling framework consists of two primary components, namely, the Structural Equations Model (SEM) and the latent segmentation model. In the SEM, the latent psychological constructs are represented as linear functions of exogenous variables with the usual stochastic error terms, while, the ordinal variables available in the data are used as indicators to the latent constructs. The results of this estimation provide us with expected values of the latent constructs which are used in the next step of the methodology to formulate the segments. Theoretically, the SEM model based on TAM to explore and model the effect of latent variables (representations of perceived usefulness and perceived ease of use given in TAM) on attitude towards using.

### Latent Segmentation

The behavioural framework employs the endogenous market segmentation approach to accommodate systematic heterogeneity in a practical manner. Individuals are assigned to segments in a probabilistic fashion based on the segmentation variables. The approach jointly determines the number of segments, the assignment of individuals to segments, and segment-specific choice model parameters. We use a multinomial logit formulation for modelling segment membership and a multinomial probit formulation for modelling segment specific choice of AV adoption. The model for willingness to adopt an AV with endogenous segmentation rests on the assumption that there are  $S$  relatively homogenous segments in the AV adoption market ( $S$  is to be determined); within each segment, the pattern of intrinsic choice preference is identical across individuals. However, there are differences in intrinsic preference patterns among the segments. Thus, there is a distinct AV adoption choice model for each segment.

## **DATA DESCRIPTION AND ANALYSIS**

Description of the sample: The data used for the analysis was obtained from American Trends Panel (ATP), created by Pew Research Center. The survey collects information about future transportation perspectives, socio-economic and demographic characteristics, and beliefs and behaviours related to automation situations. Some of the information provided by the survey data is beyond the scope of the current study, hence only those responses were considered which impact user behaviour regarding AV acceptance. We systematically removed the missing observations (with number of observations with such missing values in brackets): age category (4), marital status (2), income (70), internet-use (44), etc., and had a final dataset comprising of 3,843 observations.

Exploratory factor analysis: As a first step, relevant items were selected using an exploratory factor analysis (using the factanal package in R) before inclusion in the SEM. The internal consistency of the latent variables was also tested by calculating Cronbach's alpha coefficient ( $\alpha$ ), for which a value greater than 0.7 indicates high internal consistency. The exploratory factor analysis and the estimation of the SEM uses the R packages psych

and Lavaan, respectively. An exploratory factor analysis (following a Scree test, see Figure 1, to find appropriate number of factors, five is a logical compromise in given results) with *varimax* and *promax* rotation identifies the factors that best distinguish the sample and the observed variables with the greatest loadings. The results of the EFA are given in Table 1, only the items with a loading greater than 0.35 were retained (explanation for others is skipped to save space).

**Structural equation modelling:** The SEM model (using the Lavaan package in R, using maximum-likelihood approach) is presented in Table 2 and its schematic representation is provided in Figure 2. The CFI (= 0.977) of the model is above the threshold value of 0.9 and the RMSEA (= 0.029) is below the threshold value 0.06.

## RESULTS AND CONCLUSION

The EFA and SEM analysis results as shown below provide us a clear indication of the relationships between the proposed latent constructs. Two new constructs have been proposed in this study, which are Automation Acceptance and Response to Innovation which have rarely been looked at in motivating acceptance of Automated Vehicles. It is important to note the construct formation of Response to Innovation, based on the indicators such as impact of email, software innovation and industrial robots on individual's life, and the resulting impact of this construct on Acceptance of Automation in everyday life. This calls for further study to evaluate the causality between attitude and behavioural attributes and how one's prior experience with automation may have a short- or long- term impact on their response to Automated Vehicles. Results also show the high impact of safety perception on the constructs inferring the perceived usefulness and attitude towards use (consider adoption) of Automated Vehicles. This further strengthens the policy requirements of providing higher safety and addressing the concerns of public.

One limitation of our work concerns the direction of some relationships. The estimated models assume that attitudes influence behaviour, which is fully consistent with most leading psychological theories. Continuation of this work will not only analyse the effect of socio-demographic variables on these latent constructs, but also incorporate the association of AV adoption with residential location choice and attempt to understand and isolate the causal interplay between the two, thereby motivating the use of an ICLV model, that is, a model that combines a Structural Equation Model (SEM) to measure the latent perception of comfort and a Discrete Choice Model (DCM), based on random utility theory, to explain the residential location choice.

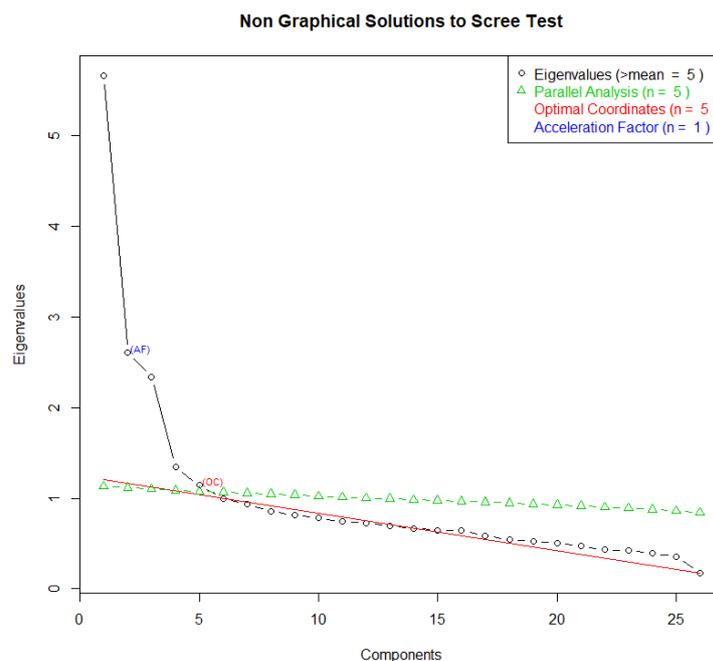


Figure 1: Scree Test to find optimal number of factors

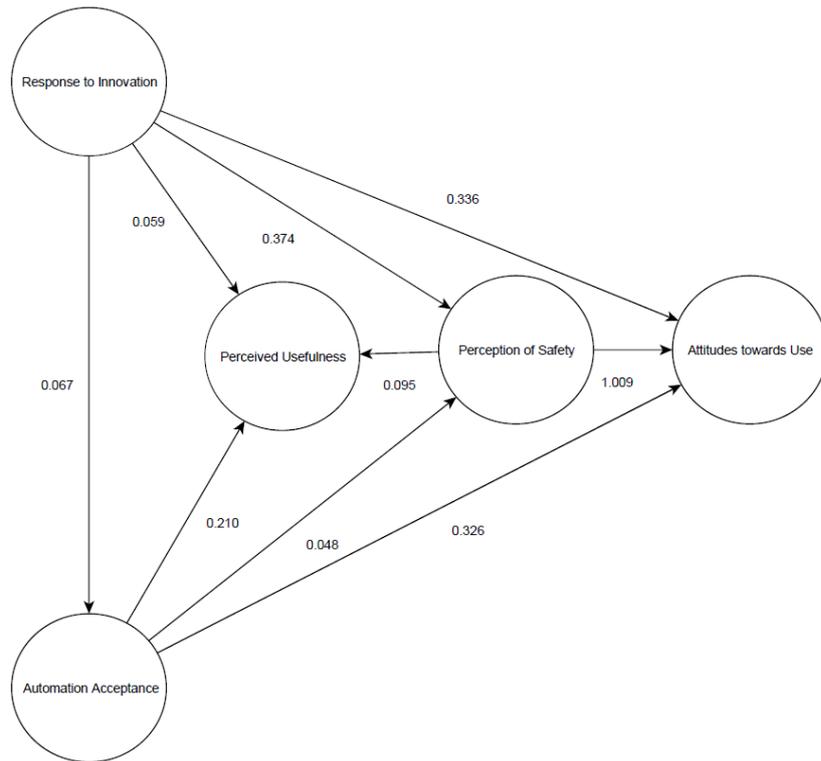


Figure 2: Schematic representation of the Structural Equations Model

Table 1: Exploratory factor analysis loadings

<i>Exploratory factor analysis loadings</i>	<i>Factor1</i>	<i>Factor2</i>	<i>Factor3</i>	<i>Factor4</i>	<i>Factor5</i>
	<i>Attitudes towards use</i>	<i>Response to Innovation</i>	<i>Automation Acceptance</i>	<i>Perception of Safety</i>	<i>Perceived Usefulness</i>
How ENTHUSIASTIC are you, if at all, about the development of driverless vehicles?	<b>0.69</b>	--	--	--	--
How WORRIED are you, if at all, about the development of driverless vehicles?	<b>0.55</b>	--	--	--	--
How safe would you feel sharing the road with a driverless passenger vehicle?	<b>0.91</b>	--	--	--	--
How safe would you feel sharing the road with a driverless freight truck?	<b>0.82</b>	--	--	--	--
Has what you've seen or heard about driverless vehicles been mostly positive, mostly negative, or a mix of both?	<b>0.44</b>	--	--	--	--
<i>If driverless vehicles become widespread:</i>					
do you think that the number of people killed or injured in traffic accidents will increase, decrease, or stay about the same?	<b>0.69</b>	--	--	--	--
which of the following do you think are likely to happen as a result? Elderly and disabled people will be able to live more independently	<b>0.42</b>	--	--	--	--
<i>Have the following technologies had a [positive impact, a negative impact / negative impact, positive impact], or no impact either way on you and your job or career?</i>					
Word processing or spreadsheet software	--	<b>0.71</b>	--	--	--
Email or social media	--	<b>0.63</b>	--	--	--
Software that manages your daily work schedule or routine	--	<b>0.68</b>	--	--	--
Smartphones	--	<b>0.70</b>	--	--	--
Technologies that help customers serve themselves on their own	--	<b>0.52</b>	--	--	--
Industrial robots	--	<b>0.41</b>	--	--	--
<i>Do you think each of the following things will or will not happen in the next 20 years?</i>					
Most stores and retail businesses will be fully automated and involve little or no human interaction between customers and employees	--	--	<b>0.65</b>	--	--
Most deliveries in cities will be made by robots or drones instead of humans	--	--	<b>0.69</b>	--	--
When people want to buy most common products, they will create them at home using a 3-D printer	--	--	<b>0.55</b>	--	--
Doctors will rely on computer programs to diagnose most diseases and determine treatments	--	--	<b>0.49</b>	--	--
<i>Would you strongly favor, favor, oppose, or strongly oppose the following rules and regulations for driverless vehicles?</i>					
Requiring them to travel in dedicated lanes	--	--	--	<b>0.70</b>	--
Restricting them from traveling near certain areas, such as schools	0.43*	--	--	<b>0.65</b>	--
Requiring them to have a person in the driver's seat who could take control in an emergency situation	--	--	--	<b>0.54</b>	--
<i>If driverless vehicles become widespread, which of the following do you think are likely to happen as a result?</i>					
Many people who drive for a living would lose their jobs	--	--	--	--	<b>0.46</b>
Owning a car would become much less important to people	--	--	--	--	<b>0.41</b>
Most people would never learn how to drive a car on their own	--	--	--	--	<b>0.39</b>

\*the variable is included in the factor where its loading is greater

-- loading not greater than 0.35, hence, not reported

Table 2: Results of Structural Equations Model

Regressions		Estimate	Std. Err.	z-value	P(> z )
<i>Attitudes towards use ~</i>					
	<i>Perception of Safety</i>	1.009	0.045	22.284	0
	<i>Automation Acceptance</i>	0.326	0.035	9.242	0
	<i>Response to Innovation</i>	0.336	0.040	8.321	0
<i>Perceived Usefulness ~</i>					
	<i>Perception of Safety</i>	0.095	0.019	5.104	0
	<i>Automation Acceptance</i>	0.210	0.025	8.400	0
	<i>Response to Innovation</i>	0.059	0.026	2.249	0.024
<i>Perception of Safety ~</i>					
	<i>Automation Acceptance</i>	0.048	0.025	1.956	0.05
	<i>Response to Innovation</i>	0.374	0.038	9.793	0
<i>Automation Acceptance ~</i>					
	<i>Response to Innovation</i>	0.067	0.025	2.710	0.007
Latent Variables		Estimate	Std. Err.	z-value	P(> z )
<i>Attitudes towards use =~</i>					
	How ENTHUSIASTIC are you, if at all, about the development of driverless vehicles?	1			
	How WORRIED are you, if at all, about the development of driverless vehicles?	0.705	0.020	35.574	0
	How safe would you feel sharing the road with a driverless passenger vehicle?	1.021	0.020	52.099	0
	How safe would you feel sharing the road with a driverless freight truck?	1.119	0.025	44.354	0
	If driverless vehicles become widespread, do you think that the number of people killed or injured in traffic accidents will increase, decrease, or stay about the same?	0.822	0.018	45.691	0
	Has what you've seen or heard about driverless vehicles been mostly positive, mostly negative, or a mix of both?	0.368	0.012	29.903	0
	If driverless vehicles become widespread, which of the following do you think are likely to happen as a result? Elderly and disabled people will be able to live more independently	0.239	0.009	25.663	0
<i>Perception of Safety =~</i>					
	Requiring them to travel in dedicated lanes	1			
	Restricting them from traveling near certain areas, such as schools	1.420	0.044	32.153	0
	Requiring them to have a person in the driver's seat who could take control in an emergency situation	0.953	0.036	26.642	0
<i>Perceived Usefulness =~</i>					
	Owning a car would become much less important to people	1			
	Many people who drive for a living would lose their jobs	0.323	0.064	5.027	0
	Most people would never learn how to drive a car on their own	0.502	0.080	6.273	0
<i>Response to Innovation =~</i>					
	Word processing or spreadsheet software	1			
	Email or social media	1.142	0.056	20.236	0
	Software that manages your daily work schedule or routine	1.118	0.059	19.039	0
	Smartphones	1.262	0.059	21.549	0
	Technologies that help customers serve themselves on their own	1.213	0.060	20.072	0
	Industrial robots	0.973	0.056	17.319	0
<i>Automation Acceptance =~</i>					
	Doctors will rely on computer programs to diagnose most diseases and determine treatments	1			
	Most stores and retail businesses will be fully automated and involve little or no human interaction between customers and employees	0.886	0.072	12.280	0
	Most deliveries in cities will be made by robots or drones instead of humans	1.420	0.058	24.488	0
	When people want to buy most common products, they will create them at home using a 3-D printer	0.735	0.062	11.919	0
<b>CFI = 0.977</b>		<b>RMSEA = 0.029</b>			

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