Hindawi
Journal of Advanced Transportation
Volume 2023, Article ID 8953109, 14 pages
https://doi.org/10.1155/2023/8953109

Research Article

Willingness to Pay for Conditional Automated Driving among Segments of Potential Buyers in Europe

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Received 18 January 2023; Revised 8 March 2023; Accepted 18 March 2023; Published 12 April 2023

Academic Editor: Zhihong Yao

This study aims to investigate the willingness to pay for conditionally automated cars (CACs) among 8,084 respondents in seven European countries by segmenting potential buyers of CACs. Future deployment of CACs depends on a sufficient willingness to pay among a sufficient large part of the population. Latent profile analysis was employed to identify the variables with the highest loadings on the latent factor "willingness to pay," based on latent constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT2) model. In addition, we analyzed which factors were associated with willingness to pay for different automated systems in CACs, i.e., for driving on urban roads, motorways, congested motorways, and parking areas. We find that a large share of respondents indicates a generally high willingness to pay for CACs, but classes with a high share of conservatives and young respondents have the lowest willingness to pay.

1. Introduction

There are a range of potential social and private benefits of higher levels of automated driving [1], and the benefits increase as the share of automated driving in the transportation system increases [2]. However, these benefits will only be realized if automated vehicles are purchased and used as intended. This requires a sufficient level of a priori acceptability and acceptance of the novel automation technology. A priori acceptability differs from acceptance of CACs. Acceptability refers to an individual's reactions toward the novel vehicles before having used it, whereas acceptance refers to reactions towards CACs after having used it. Furthermore, acceptance of automated driving also requires that potential owners/users of the vehicles have a sufficient willingness to pay for these vehicles. In this paper, we study the willingness to pay for conditionally automated cars (CACs), and how classes of potential buyers of CACs can be identified. The conditional automated driving corresponds to SAE automation level 3, where the vehicle performs all driving tasks within the operational design domain (ODD), but the driver is required to take control of the driving when needed and when driving outside its ODD. In SAE level 4 (full automation), there is no need for driver intervention.

We study consumers' willingness to pay for autonomous vehicles for several reasons. First, a range of benefits stemming from using CACs will only be realized if a sufficient adoption of the novel technology takes place. Second, understanding which groups of consumers are willing to pay for automated vehicles, and to what extent they are willing, is imperative for market communication with potential buyers and users of CACs. Third, we seek to aid public authorities when designing standards and, e.g., information campaigns for automated vehicles in order to realize the benefits from automated driving.

1.1. Background and Existing Research. A major reason for the benefits stemming from the use of automated vehicles relates to the way they reduce reliance on human driving skills. Human error is estimated to be the main reason for 94% of fatalities [3], and according to the most optimistic estimates, automated vehicles have the potential to reduce fatalities by 90% by eliminating accidents caused by human error, as stated by Evans [4] Fleetwood [5]. Safety is, therefore, an important aspect of the initiatives involved in regard to designing and manufacturing vehicles with higher automation levels today.

Automated vehicles have the potential to provide a range of benefits, both societal and private. The societal benefits range from safety of the overall traffic system to environmental gains [1, 2]. Automated driving may potentially reduce risky and dangerous driving behavior, thereby reducing accidents and injuries, and improving road safety (for a review see [6]). Automation contributes to maintaining a safe distance between vehicles, reducing the number of crashes and stop-and-go waves, thus reducing congestion. When the number of traffic jams and stop and go waves falls, fuel use decreases, and environmental gains may be obtained from the reduced emission of greenhouse gases [7, 8]. Related to reducing congestion and traffic jams is automated driving's ability to increase road capacity [9, 10]. All such factors have the potential to contribute substantial societal benefits as the penetration of automated vehicles increases [2]. However, indirect impacts, e.g., increased car usage from higher penetration of automated vehicles, may increase congestion and associated harms.

There are also potential private benefits from using automated vehicles. Car owners may see the potential for saving money if increased road safety brings about fewer crashes and reduced bills for medical treatment and vehicle repair costs [3]. Automated driving may increase productivity by transforming travel time into more valuable time use, e.g., by allowing people to work while traveling by car [11] see also Potoglou et al. [12]. People with disabilities may become self-sufficient, where automated driving can assist them in their everyday life, hence facilitating greater independence for, e.g., seniors and individuals with disabilities [13, 14].

While the list of potential benefits of automated driving is long, one potential barrier to buying and using them is the cost of purchasing automated vehicles. Hence, the focus of the present study is on willingness to pay (WTP) for CACs. Our research is divided into three interrelated questions, all involving aspects relating to willingness to pay for CACs, and to what extent one can identify classes of consumers expected to have a high willingness to pay for CACs. At the first level, market penetration requires a positive willingness to pay for CACs. However, a range of studies find that a significant share of potential buyers of automated vehicles does not have a positive willingness to pay for these vehicles. In an early international study, Schoettle and Sivak [15] investigated respondents' willingness to pay for higher levels of automated driving. They found that the majority of respondents in the USA (55%), the UK (60%), Australia (55%), and Japan (68%) were not willing to pay additionally for this technology. However, the share of respondents not willing to pay more was lower in China (22%) and India (30%). In a recent study covering eight European countries [16], the willingness to pay for CACs was found to be higher than Schoettle and Sivak [15] found it to be in the USA, the UK, Australia, and Japan. In Nordhoff et al. [16]; only around 30% were not willing to pay extra.

At the second level, we are interested in understanding how much people are willing to pay for CACs. The results from existing literature on this topic are mixed. Payre et al. [17] found, in a study of 421 French drivers, that there was a significant positive willingness (up to €10,000) for automated cars compared to traditional cars. Daziano et al. [18] found an average willingness to pay for partial/conditional automation ($3,540) and even more for full automation ($4,900).

At the third level, we are interested in aspects relating to the question: what are the characteristics of people willing to pay a price premium? A premium refers to a higher price for a CAC than a traditional car. Existing research has examined a range of potential explanatory variables explaining (lack of) willingness to pay, e.g. sociodemographic variables (see Gkartzonikas and Gkritza [19] for an overview). A study of intention to use CACs in eight European and nine non-European countries found that intention to use CACs was highest amongst younger and male respondents [20] and the trends varied widely across countries.

Despite existing research in these areas, our knowledge about the classes of consumers (not) willing to use or buy CACs is still highly restricted. Enhanced knowledge about the unwillingness to purchase and use CACs may be beneficial both for private entities and public authorities. Private entities, such as car manufacturers and retailers, may use such information for market communication and design of vehicles. The authorities may use this knowledge in the design of policies related to CACs. Public authorities may play a key role in communicating objective information about the advantages and disadvantages of using automated vehicles. When, e.g., designing policies related to autonomous vehicles, it is important to understand how potential consumers perceive the benefits and risks involved when purchasing and using automated vehicles.

Similar questions have been analyzed in König and Neumayr's study [21]. They studied the attitudes and potential barriers of end-users in regard to using self-driving vehicles. The most severe concern was the fear of attacks from hackers, while concerns regarding system safety, confusion of technology in unprecedented situations, and fear of technical problems were also found. As noted in Reimer's study [22], if an individual does not trust the technology, this person is more likely to turn it off, thereby losing the potential benefits of using the technology. Finally, our study focus is on CACs, vehicles that are expected to enter the market in the not too distant future. Hence, information about WTP is of great interest.

1.2. Objectives. In order to study how willingness to pay for automated vehicles may vary between various segments of the population, we utilized a large-scale survey among around 8,100 respondents in seven European countries. We apply the UTAUT2-framework (Venkatesh et al. [23]) using a set of questions explaining the six latent constructs, performance expectancy, hedonic motivation, effort expectancy, facilitating conditions, social influence, and behavioral intent. The questions in the survey are based on the items used in the study of Venkatesh et al. [23], and hence designed with the intent to generate latent constructs in UTAUT2. Details are given in Section 2.2.

Our primary research question relates to studying if and how classes of consumers differ when it comes to willingness to pay for CACs. To answer the main research question related to willingness to pay, we investigate the following aspects of potential buyers of CACs:

(1) Identify different classes of consumers with respect to the UTAUT2-constructs and their attitudes towards using and purchasing CACs
(2) Describe the classes of consumers with reference to the latent variables from the UTAUT2-framework and demographic variables
(3) Describe the classes of consumers using variables that measure expected user experiences with the intent to further understand why consumers are resistant/nonresistant to using a novel technology such as CACs

Our study aims to add to the literature on willingness to pay for conditionally automated cars along two dimensions. First, we propose to use a novel methodology combining latent profile analysis and the UTATU2 framework. Second, our analysis is also novel in that the data from the surveys consist of large samples of respondents (around 8,100) covering different regions in Europe.

The methodology and findings from this large-scale study could be valuable for both vehicle manufacturers/business owners and public authorities. Vehicle manufacturers may gain additional knowledge about potential buyers of CACs. The methodology may also be applicable in business intelligence systems analysis. The authorities could also use the results from this study to design information campaigns for promoting the new automation technology, thereby increasing the realization of societal benefits from automated driving.

The rest of the paper is organized as follows: first, we outline the data and methodological and empirical framework using latent factor analysis and latent profile analysis for preclassification of respondents. Section 3 reports the results with details on the demographic and attitudinal variables for classes of respondents and investigates their willingness to pay for CACs. Sections 4 and 5 provide discussion of the results, policy recommendations, and conclusions.

2. Data and Methods

The present study is part of the EU H2020-funded L3Pilot project (https://www.l3pilot.eu), which carried out large-scale pilots of conditionally automated passenger cars (SAE level 3 automation) on public roads in Europe with the aim of investigating their technical abilities, user experience, user acceptance, and their potential socioeconomic impacts. As part of the L3Pilot project, online multinational surveys were conducted in seven European countries intending, among other purposes, to elicit behavioral intention to use and willingness to pay for conditionally automated cars. The data from these surveys are used for the analyses in this study.

In the following, we outline the data used for the analyses and provide an overview of the methodological approach and empirical methods chosen for analyzing how potential users of CACs differ in their intention to use and willingness to pay for CACs.

2.1. Data. The data for the analyses originate from an online questionnaire administered to around 8100 respondents from seven European countries. The data were collected between April 2019 and June 2019 in France, Hungary, Italy, Germany, Sweden, and the UK, and in March 2020 in Spain. These countries were selected on the basis of their geographical representation within Europe and the size of their car market share. In each country, a sample that was representative of the age, gender, and income distribution of its population was selected. The respondents received either financial compensation or a voucher (one Euro) for completing the questionnaire. All respondents held a driver's license. The survey contained questions about the respondents' sociodemographic status (age, gender, education, and income), familiarity with advanced driving assistance systems, their understanding of the concept of CACs, attitudes toward CACs, and their willingness to pay for automated system-specific features of CACs, i.e., for automated driving on urban roads, motorways, congested motorways, and parking areas. Outliers and respondents with unidentified gender or identified as "other" were omitted, thereby resulting in 8,084 observations in total for the study sample.

2.2. Methodological Approach. In order to study how willingness to pay for automated vehicles may vary between various segments of the population, our theoretical basis rests on the UTAUT2-framework (Unified Theory of Acceptance and Use of Technology) (Venkatesh and Davis [24] Venkatesh et al. [23]). UTAUT assumes that an individual's behavioral intention to use a technology is influenced by performance expectancy (the degree to which the technology is perceived to be useful), effort expectancy (the degree to which the technology is perceived to be easy to use), social influence (the degree to which the technology is appreciated in social networks of importance to the individual), and facilitating conditions (the individual's perception of their possession of the resources required to use the technology) (Venkatesh and Davis [24]). UTAUT2 suggests that the intention to use a novel technology is also influenced by hedonic motivation (the degree to which the technology is perceived to be enjoyable) (Venkatesh et al. [23]). The UTAUT2-framework is illustrated in Figure 1.

Latent profile analysis (LPA), also referred to as latent class analysis, is one of several submodels of the structural equation model (SEM) framework, intended to elicit groups of respondents from multivariate categorical data (see Masyn [25] for an overview). We use the term "latent profile analysis" (LPA), which is often referred to as latent class analysis (LCA). Strictly speaking, LCA is used when applying categorical variables, and LPA when using continuous variables, as shown in this paper. The groups of respondents are called "latent classes." This approach resembles cluster analysis. However, the LPA-framework allows for statistical evaluation of alternative specifications and models. Most statistical techniques take for granted some degree of homogeneity among the studied population, and then proceed to analyze the statistical properties of the population as a whole. When using LPA, we use a categorical latent variable to represent groups of respondents referring to these groups as classes. Importantly, these groups are not established on the basis of respondents' self-designations. Rather, using constructs measured by the questionnaire, groups are established on the basis of statistical correlations and trends that indicate commonalities among segments, and these segments can then be assessed in terms of other variables to understand the potential drivers of segmentation. Hence, while many studies on automated driving segment respondents according to sociodemographic variables (sex, age group, etc.) or other observable traits, our study segments respondents according to the latent factors in the UTAUT2-framework. UTAUT2 outlines a set of factors affecting individuals' willingness to use a novel technology (here, CACs). This study recognizes that various factors will be of varying levels of importance for different users, and then investigates how these user segments differ in terms of their WTP and sociodemographic variables.

We apply the UTAUT2-framework by using a set of questions explaining the six latent constructs: performance expectancy, hedonic motivation, effort expectancy, facilitating conditions, social influence, and behavioral intent. The questions in the survey are based on the items used in Venkatesh et al. [23], and hence designed with the intent to generate latent constructs in UTAUT2. The questions are listed in Appendix A. These questions have been studied and tested in a range of different settings, establishing the validity of the questions used in the survey for constructing the latent variables (Nordhoff et al. [26]; Zheng and Gao [27]; Jun et al. [28]); Tamilmani et al. [29]). We, therefore, use only confirmatory factor analysis to determine which questions are to be included in the latent constructs. Since we use factor analysis for prediction, it is necessary to include at least three (and preferably four) items (see Hair et al. [30]). Therefore, the use of items in our study differs from that of Nordhoff et al. [26]. In the second stage, we estimate latent classes of consumers using latent profile analysis. We use the latent constructs from the first part to classify respondents into different classes of respondents, or potential buyers of CACs. Finally, we describe the latent classes using demographic and psychological variables.

2.2.1. Latent Factor Analysis. In the questionnaire, all respondents answered every question for each latent factor in the UTAUT2-model (see Appendix A). These questions are analyzed using factor analysis. This enables us to include the relevant questions and exclude the irrelevant ones in the survey. The statistical fit for the questions used in the latent constructs is analyzed using five measures for evaluating to what extent the questions fit the latent construct.

The factor loadings (Coef.) for all questions and their respective standard errors (Std. Error) are reported in Table 1. Hair et al. [30] suggest that factor loadings should not fall below 0.5 and ideally be higher than 0.7. The item-rest correlation is also reported in Table 1 (I-R corr.), and documents the correlation between values for one particular question, question i, and all other questions in the latent construct except question i. Second, the item-based Cronbach's alpha (Alpha) is also reported in Table 1. According to Nunnally [31], the overall Cronbach's alpha should not be below 0.8 in applied research (or 0.9 when important decisions depend on it).

The two first latent constructs can be referred to as "value" latent constructs, performance expectancy, and hedonic motivation. These latent constructs indicate the perceived value of using CACs, how the use of CACs in one's daily life produces benefits for respondents either via performance expectancy or via joy of use (hedonic motivation). The overall Cronbach's alpha for the latent construct performance expectancy is 0.889, while for hedonic motivation it is 0.868.

The next two latent variables in the UTAUT2-framework are learning latent variables, referred to as effort expectancy and facilitating conditions. These variables intend to indicate to what extent the respondents feel they have the necessary knowledge (effort expectancy), or the extent to which they are able to access the required knowledge (facilitating conditions) to use CACs. The overall Cronbach's alpha for effort expectancy is 0.784, while that for facilitating conditions is 0.790. These latent constructs are lower than, but close to, the desired level of 0.8, as in Nunnally [31]; and therefore used in the analysis.

The latent construct effort expectancy is slightly weaker than the other constructs above. However, exclusion of any of the questions in the construct will reduce the construct's significance further. All questions are, therefore, included in the analysis of latent classes.

The final latent construct relates to the social characteristics of the respondents (social influence), which reflects other people's influence on the respondents, when it comes to using and purchasing a CAC. The overall Cronbach's alpha for all questions is 0.868.

The final factor used as an indicator for latent classes in our UTAUT2-framework is the respondents behavioral intent. This latent factor intends to reflect how likely the respondent is to use the novel technology once it is available. All questions are retained in the latent construct since the overall Cronbach's alpha for all questions is 0.868.

On the basis of the construction of the five latent constructs above, all respondents are assigned a numerical score for all latent constructs. Having outlined the identification of questions to be used when generating latent factors, we turn to

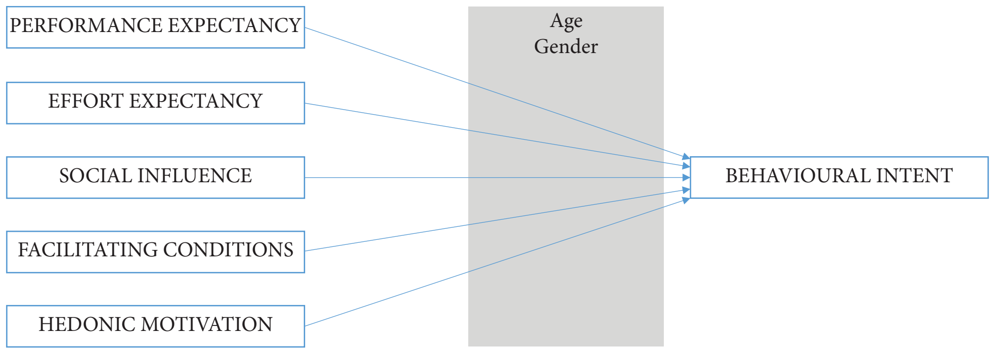

Figure 1: Illustration of the UTAUT2-framework and its latent constructs. Items in gray are predictors of class types.

Table 1: Statistical fit for questions, leading on to the latent variables.

Item	Coef.	Std. error	I-R corr.	Alpha
Performance expectancy (PE)				
PE1	0.798	0.005	0.735	0.850
PE2	0.791	0.005	0.728	0.853
PE3	0.818	0.005	0.753	0.844
PE4	0.818	0.005	0.753	0.843
Hedonic motivation (HM)				
HM1	0.761	0.006	0.689	0.819
HM2	0.851	0.005	0.746	0.766
HM3	0.815	0.006	0.724	0.786
Facilitating conditions (FC)				
FC1	0.773	0.007	0.653	0.726
FC2	0.686	0.008	0.603	0.749
FC3	0.746	0.007	0.632	0.735
FC3	0.618	0.008	0.550	0.776
Effort expectancy (EE)				
EE1	0.764	0.008	0.633	0.682
EE2	0.688	0.008	0.588	0.730
EE3	0.754	0.008	0.627	0.689
Social influence (SI)				
SI1	0.798	0.006	0.718	0.781
SI2	0.784	0.006	0.691	0.793
SI3	0.800	0.006	0.708	0.785
SI4	0.647	0.008	0.590	0.837
Behavioral intent (BI)				
BI1	0.861	0.005	0.774	0.800
BI2	0.784	0.006	0.716	0.825
BI3	0.755	0.006	0.691	0.834
BI1	0.738	0.006	0.670	0.844

the identification of latent classes among the respondents. All latent factors in the UTAUT2-framework were constructed using confirmatory factor analysis (SEM), followed by the predict factor postestimation command in Stata. This command produces factor scores, in this case, by the regression method. Next, we use the numerical scores to create classes of respondents using latent profile analysis.

2.2.2. Latent Profile Analysis. The choice of the number of classes, enumeration, is important in LPA. However, there are no strict rules regarding how many classes to choose. On the one hand, there are various statistical measures used to assess the statistical significance of models with different numbers of classes. On the other hand, increasing the number of classes may reduce the economic significance of the model. For instance, as the number of classes increases, the number of respondents classified into different classes decreases, and hence, the statistical power may fall as well. In addition to this, as the classes become smaller, the analysis will to a larger extent involve niche segments of the population.

In Table 2, we document the AIC (Akaike information criterion) and BIC (Bayesian information criterion) statistics for the models for up to 10 classes. As evident, these statistics fall as the number of classes increases (with a few exceptions).

The changes in information criteria as the number of classes increases is not large, thus the statistical fit does not change much when using different number of classes in the model. If we were to choose more than five classes, two of them would be small (one less than 5% of the respondents). Therefore, we choose to analyze the data with five classes of consumers.

3. Results

3.1. Classes of Consumers. In this section, having analyzed the data using latent factor analysis and latent profile analysis, we document the results of the analyses conducted. However, before turning to the results, a short discussion on the names used for the five classes is given. There are no strict rules regarding the "naming" of the classes in these types of analyses. We have used the information on how the chosen classes score on the UTAUT2-factors and demographic variables (sex and age) to characterize the classes rather than using numbered designations. The respondents assigned to the largest class have been characterized as the "typical" class. The names of the youthful and old-school classes rest on the age composition of these groups, while the naming of the conservative and enthusiast classes is based on the scoring on the UTAUT2-factors. The inclusion of age and gender as predictor variables may impact the assignment of respondents to the various consumer classes, in particular, the youthful and old-school classes of consumers (see Masyn [25] for discussion).

Table 2: Statistics for determining the optimal number of classes in seven European countries.

Classes	N	df	AIC	BIC
3 classes	8.084	41	51.949,00	52.235,63
4 classes	8.084	54	50.552,00	50.930,03
5 classes	8.084	67	49.270,00	49.738,42
6 classes	8.084	80	49.424,00	49.984,11
7 classes	8.084	93	48.503,00	49.153,44
8 classes	8.084	106	48.109,00	48.851,07
9 classes	8.084	119	47.885,00	48.718,20
10 classes	8.084	132	47.516,00	48.440,06

N: number of observations; df: degrees of freedom.

As shown in Table 3, the typical class contains the largest share of respondents (41%). The enthusiast class is the second largest, and the old-school class is the third largest. The enthusiast and youthful classes are smaller, just above 6%. We also see that the confidence intervals for the classes are quite narrow, and all p values are below 0.05. Thus, class affiliation of the respondents when using five classes of potential buyers of CACs seems to be very stable.

3.1.1. Description of Classes. Since the typical class accounts for 41% of the respondents, the other classes are evaluated relative to this particular class.

The first thing to note is that the classes score similarly on both latent constructs related to value, performance effort, and hedonic motivation (see Figure 2).

The conservative class scores very negatively in regard to the two value constructs, performance effort, and hedonic motivation. Hence, the conservative class does not expect to experience high values from using these vehicles. We also note that the enthusiast class is very positive along both value constructs. The score is significantly higher than all other groups, indicating that the enthusiast class expects to experience an especially high value from both the practical daily usage of CACs and from the hedonic joy of using such cars. The typical, youthful, and old-school classes differ less than the two classes discussed above, but the differences are, nevertheless, still statistically significant. While the typical class scores slightly negatively on the value constructs, the youthful class scores slightly positively. These three classes, the typical, youthful, and old-school classes, score more on the neutral side than on the latent construct. This contrasts with the conservative class, expecting a low value, and the enthusiast class, expecting a high value from the use of CACs. It should be noted that, although there is a high correlation between these two measures of value, the two latent constructs measure different aspects of using CACs. The latent construct performance effort measures the value of using CACs in one's daily life, while hedonic motivation measures to a greater extent the intrinsic pleasure of using such vehicles.

When analyzing the learning latent variables, effort expectancy and facilitating conditions, slightly different results emerge (Figure 3).

Table 3: Classes of consumers; share and statistical fit.

Classes	Share	Std. error	95% confidence interval	
Typical	0.410	0.012	0.387	0.434
Conservative	0.062	0.005	0.053	0.072
Youthful	0.068	0.007	0.054	0.081
Enthusiast	0.161	0.011	0.141	0.182
Old-school	0.298	0.014	0.271	0.325

The first thing to note is that the typical class has the lowest score along these two dimensions. Thus, this is an indication that the general public expects that it will be difficult to learn to use a CAC. Second, while the old-school class scores higher than the typical and conservative classes, the enthusiast class scores slightly lower on the learning latent constructs. The respondents in the enthusiast class expect that they will find it easy to obtain the knowledge required for using CACs, and more so, they expect to easily find the necessary information and knowledge about CACs. It should be noted that the latent variable effort expectancy relates to a direct measure of using these novel vehicles, e.g., the easiness of usage. This contrasts with the latent construct facilitating conditions, which measures how easily respondents expect to obtain the knowledge required to use these cars.

Finally, the social latent variable is outlined as for the two cases in Figure 4.

The primary aspect to note when analyzing the social latent constructs, compared to both the value and learning latent constructs, is that the conservative and youthful classes' scores obtain a very negative score compared to the other classes. The typical class obtains a neutral score, while the enthusiast and old-school classes attain positive values. This construct, given the items used, relates to the extent to which the respondents feel social expectations to use CACs from people deemed important or influential in their social networks.

3.1.2. Classes and Demographic Variables. Having described the classes identified by the latent profile framework using the latent constructs from the UTAUT2-framework, we illustrate how the classes differ in regard to the demographic variables, i.e, age, gender, income level, and education.

The four graphs shown in Figure 5 illustrate a density plot of the distribution of age for the respondents in the survey (see Table 3). The horizontal axis measures the age of the respondents, while the vertical axis measures the share of respondents for each age group in the sample. The red line in all four graphs represents the distribution of age for the typical class (the class comprising the largest number of respondents). This class is used as a base class, shown in red lines. All the other classes, which are shown in blue lines, are compared to the base class. The shaded area provides the 95% confidence interval for the classes. Note that the red line and shaded area are representing the typical class and are identical for all four graphs.

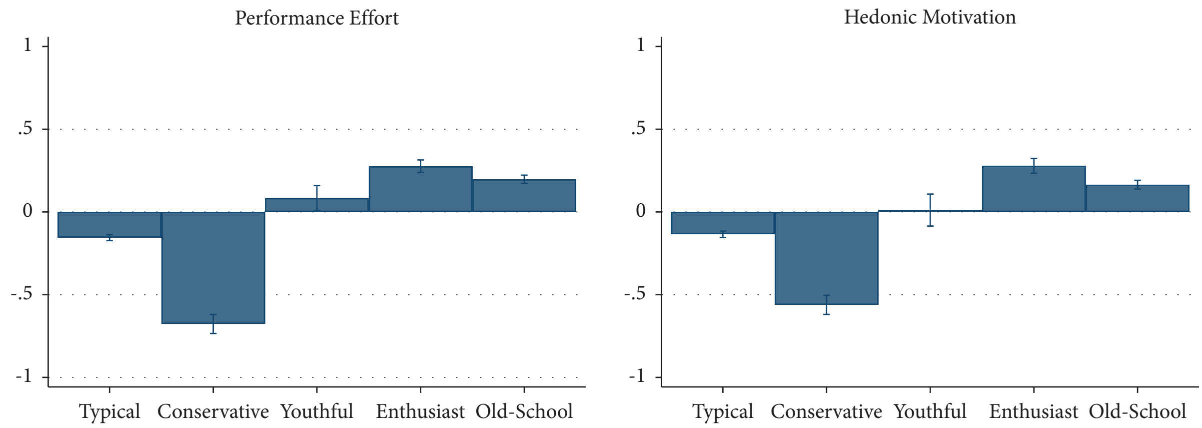

Figure 2: Value latent constructs: performance effort and hedonic motivation. Latent factor scores on vertical axis. Four items used for generating the PE-latent variable: it is expected that a CAC would be useful in meeting daily mobility needs; using a CAC would help reach the destination more safely; using a CAC would help reach the destination more comfortably; it is assumed that a CAC would be useful in daily life. Three items used for generating the HM-latent variable: using a CAC would be fun; using a CAC would be entertaining; using a CAC would be enjoyable.

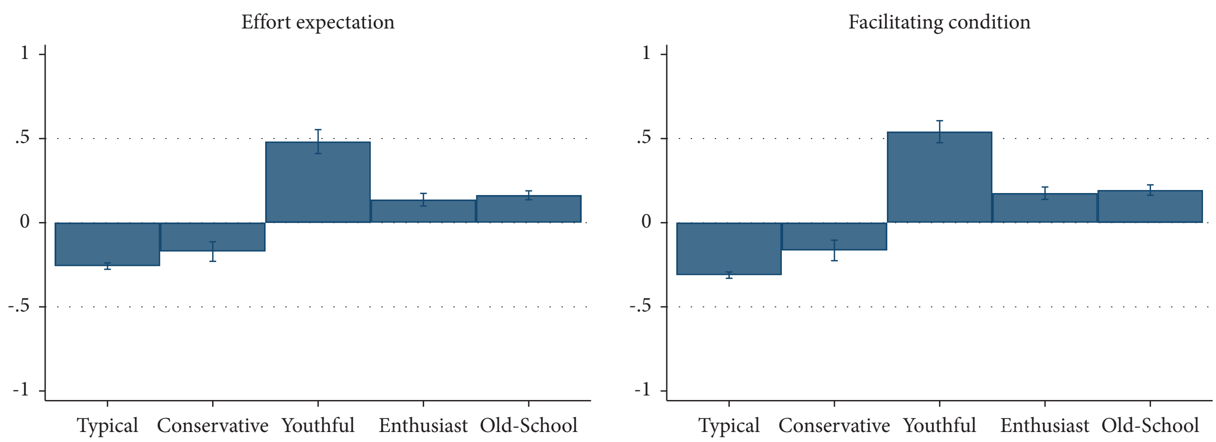

Figure 3: Learning latent constructs: effort expectancy and facilitating conditions. Latent factor scores on vertical axis. Four items used for generating the EE-latent construct: learning how to use a CAC would be easy for me; it is expected that a CAC would be easy to use; it would be easy to become skillful at using a CAC; a CAC is recommended to others. Four items used for generating the FC-latent constructs: acquiring the necessary knowledge to use a CAC; it is expected the use of a CAC to be compatible with other digital devices that is used; it is expected to have the necessary knowledge to use a CAC; it is expected to get help from others while having difficulties using a CAC.

Observing the upper left graph, the conservative class seems to be similar to the typical class. However, the conservative class has a lower share of respondents in the age group between about 25 years and 35 years. The conservative class has a higher share of respondents at age 18 to about 20, when compared to the typical class. When inspecting the upper right graph, we see that the enthusiast class has a high share of relatively older respondents and a lower share of younger respondents. From the lower left graph, we see that the youthful class has a very high share of respondents aged between 18 and about 30 and a lower share of older respondents. Additionally, the old-school class has a high share of older respondents and a particularly low share of young respondents. We also see that this result is highly significant. Moreover, noteworthy is the striking contrast in age distribution between the youthful class, on the one hand, and the old-school and the enthusiast classes on the other.

3.1.3. Classes, Gender, and Income Categories. The shares of female and male respondents differ among the classes (Table 4). The typical class has the highest share of female respondents at 53%, followed by the old-school class with 51% and the youthful class with 49%. The conservative class (43%) and the enthusiast class (38%) have the lowest shares of female respondents. Such gendered differences in feelings towards using automated cars have also been found in the literature previously, as stated by Hohenberger et al. [32].

Income was categorized from 1 to 6, indicating the lowest to highest income levels. In order to take account of the income differences between the high- and low-income countries in the surveys, the categorization of income levels was based on the average national income in respective countries. As evident, the respondents also differ in regard to income (Table 5). The old-school and typical respondents

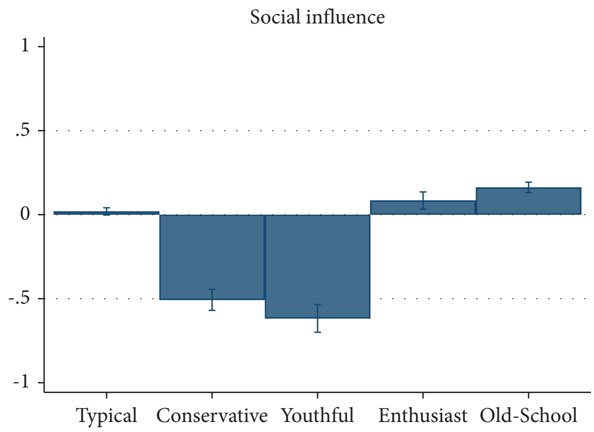

Figure 4: Social latent construct: social influences. Latent factor scores on vertical axis. Three items used for generating the SI-latent construct: it is assumed that people whose opinions is valued would prefer that a CAC is used; it is expected that people who influence behaviour think that a CAC should be used; it is expected that people who are important think that a CAC should be used.

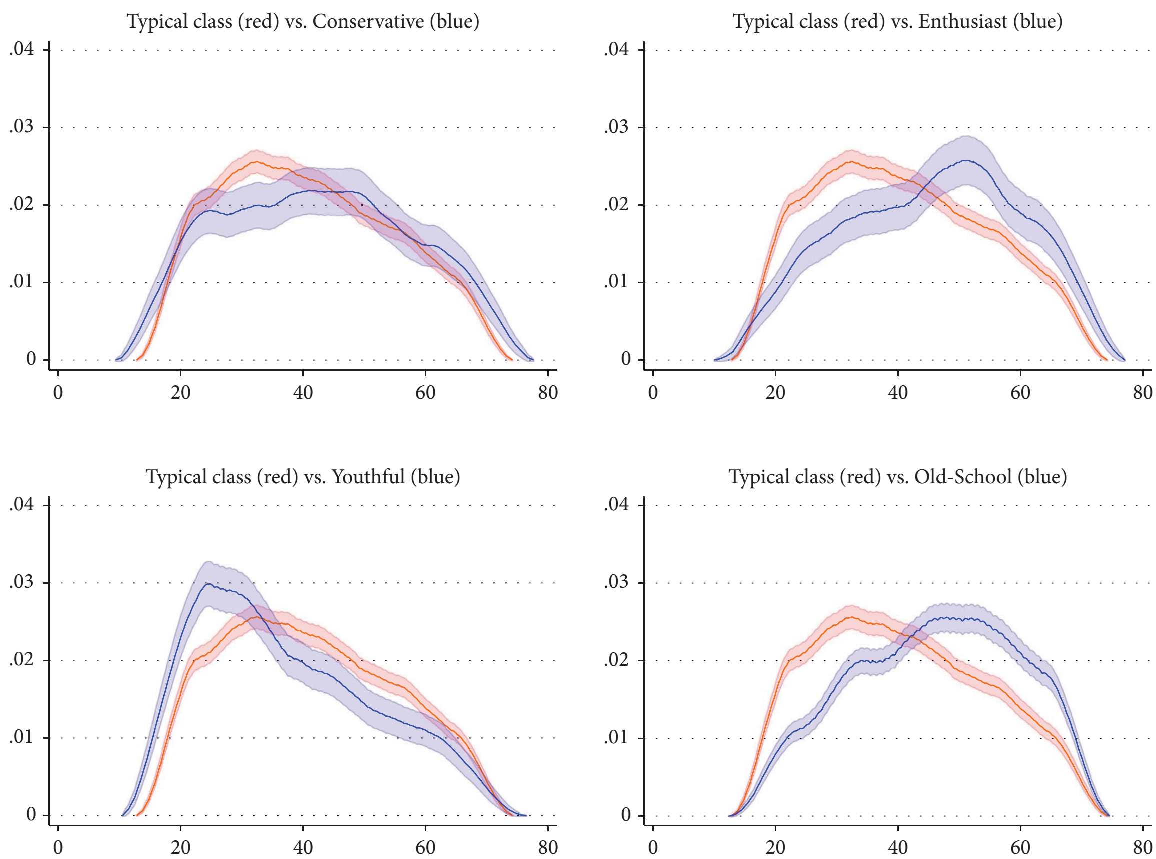

Figure 5: K-density plot of age distribution of classes of respondents. Age measured along the horizontal axis; share of respondents along the vertical axis.

demonstrate higher mean incomes, while the youthful class scores lowest on this dimension.

3.2. Classes and Their Willingness to Pay. We will now turn our focus to how the classes differ in regard to willingness to pay for CACs. Four measures of willingness to pay for CACs for each automated driving function (ADF) were used: automation on motorways, automation on congested motorways, automation on urban roads, and finally, using automation for parking. In the questionnaire, respondents were asked to indicate how much extra they would be willing to pay for these ADFs. In order to make sure that the respondents were aware of the specific features of each

Table 4: Share of female respondents.

	Typical	Conservative	Enthusiast	Youthful	Old school
Share female	0.53	0.43	0.38	0.49	0.51

automated driving function, i.e., in which conditions the systems could operate, they were given relevant information regarding each ADF before answering the WTP questions. The response options were given on a Likert scale from 0 to 7, where respondents could choose 0 if they were unwilling to pay any extra amount for an automated driving system, or a price between 1 to 7, representing the lowest to highest price categories.

The average WTP for all four automated driving functions is provided in Figure 6.

We see that the largest class (typical) has the highest WTP, followed by the enthusiast and old-school classes. The youthful class and the conservative class have the lowest average WTP for the four driving functions. These two latter classes are also the smallest classes in our sample, consisting of about 13% of all respondents.

For estimating the classes of respondents, we used the latent construct behavioral intent as the explanatory variable. A natural continuation of this analysis is to investigate how behavioral intent affects the willingness to pay for the CACs. In Figure 7, the willingness to pay for using CACs on motorways, congested motorways, urban roads, and for parking areas, is illustrated.

The group referred to as conservative scores very low on most measures of willingness to pay. This is as expected, since this class scored fairly low on the latent constructs, performance effort and hedonic motivation. This class also scores highly negatively on the social influence construct, indicating that these respondents do not expect their peers to prefer them to use CACs. Hence, the respondents in the conservative class do not foresee getting any value from buying (or using) CACs, which may partially explain their lack of willingness to pay for these vehicles.

Furthermore, the old-school class also has a relatively low willingness to pay for CACs. Along most latent constructs, these respondents score neutrally, except for the learning variables where these respondents expect it to be easy for them to learn (or obtain the knowledge required to learn) how to use CACs. Although these respondents score neutral on the value constructs, the score of these latent learning constructs strongly indicates that learning is expected to be easy, or that the cost of learning is expected to be low. Hence, the two classes with relatively older respondents seem to have lower willingness to pay than what the classes with relatively young respondents have. Age is found to affect willingness to pay in previous studies, as stated by Abraham et al. [33].

The youthful and enthusiastic classes, respectively, score about the same on all measures of willingness to pay, and none of the differences are statistically different. It is very easy to explain the relatively high willingness to pay for CACs for the enthusiastic class. These respondents expect that CACs will be both highly beneficial in everyday use and enjoyable to use these vehicles. Although the youthful class also scores relatively high on these latent constructs, it is significantly lower than the enthusiasts. Similarly, enthusiasts expect to find it easy to obtain the required knowledge for learning to use CACs. This is less true for the youthful class, which scores neutral along this dimension.

What is not as expected, following the discussion of latent constructs for the identified classes, is that the typical class has a willingness to pay for CACs that is equally as high as the youthful and enthusiast classes. This is the case even though the class scores relatively low on the value constructs, with only the conservative class scoring lower. In addition, the typical class respondents expect that it will be difficult to learn to use a CAC and/or to get access to the knowledge required to learn to drive CACs. However, this class scores positively on the social influence scale. The latter result is promising for the car manufacturers. Although the largest share of respondents scores relatively low in regard to the expected value of CACs in everyday life, and expects that it will be relatively difficult to obtain knowledge to operate these vehicles, this group has quite a high willingness to pay for CACs.

3.2.1. Attitudinal Measures. Figures 8–10 illustrate the average scores of the identified classes on a range of different attitudinal measures while traveling by CACs, and reporting the mean willingness to pay across the four ADFs (motorways, congested motorways, urban roads, and parking areas) on the horizontal axis. All attitudinal variables are listed in Appendix B. Response options were given on a 5-point Likert scale (strongly disagree to strongly agree). The result seems to confirm the previous results, with only a few exceptions. These variables measure to what extent respondents trust the use of CACs, and to what extent the respondents expect the vehicles to work as expected.

In what follows, we will discuss how the attitudinal questions vary between and within classes of consumers.

The results are mixed for the attitudinal variables related to feelings when operating a CAC, as measured by questions relating to “feeling comfortable,” “feeling relaxed,” “feeling safe,” and “trust.” The conservative class has a relatively low WTP (Figure 6), and scores are also lowest on all attitudinal variables relating to the feeling of comfort and safety (Figure 8). On the contrary, the youthful class with the lowest score on WTP scores high on feelings related to attitudes toward using the CACs. This result may be explained by the fact that the youthful class has relatively low income levels compared to other classes.

A similar pattern emerges when looking at questions related to how wary the respondent would be with respect to incidents caused by other road users’ behavior or the potential for car system failure (Figure 9). The classes conservative and enthusiast score relatively low, while the classes typical, youthful, and old-school score relatively higher.

Table 5: Classes of consumers and income categories.

	Typical	Conservative	Enthusiast	Youthful	Old-school
Mean income cat	4.24	4.15	4.49	4.10	4.39

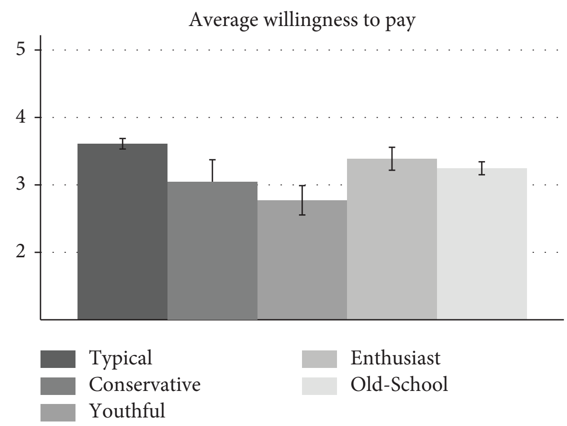

Figure 6: Average willingness to pay for CAC with all automated driving functions (motorways, congested motorways, urban roads, and parking areas). Thin vertical lines represent the 95% confidence interval.

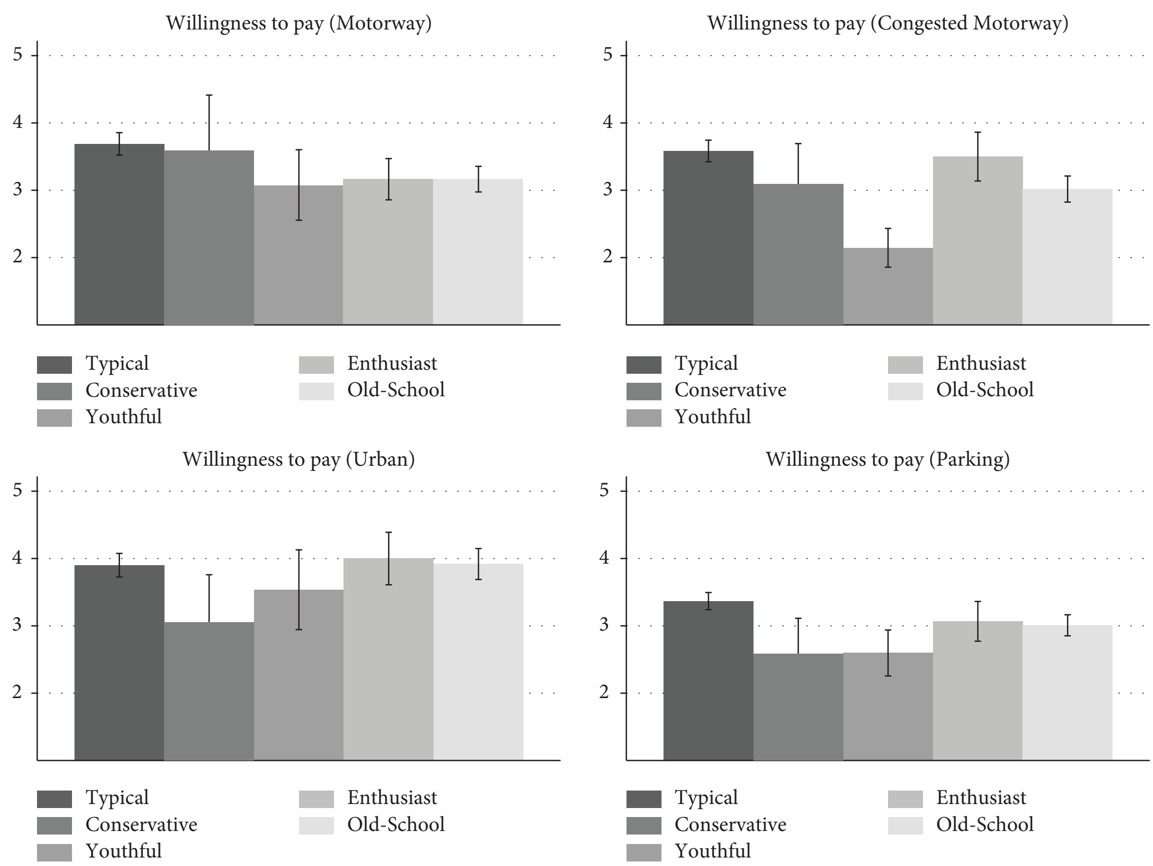

Figure 7: Willingness to pay for CAC for each automated driving function. Thin vertical lines represent the 95% confidence interval.

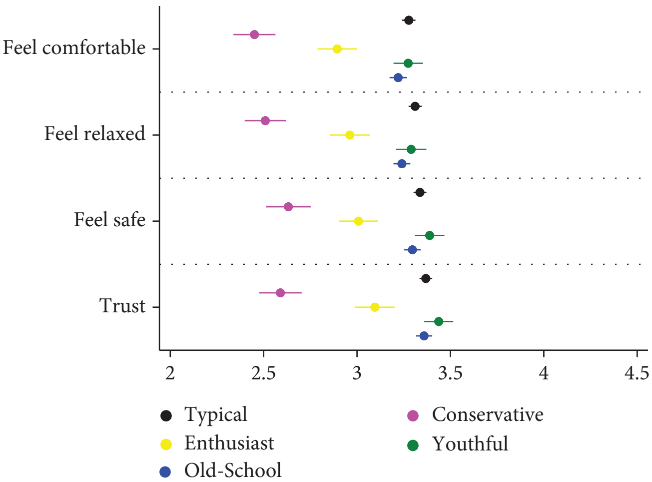

FIGURE 8: Mean values of attitudinal variables with 95% confidence interval by consumer classes. Measured items on the vertical axis: I would feel comfortable giving control to a CAC; I would feel relaxed giving control to a CAC; I would feel safe using a CAC; I would trust a CAC for my everyday travel.

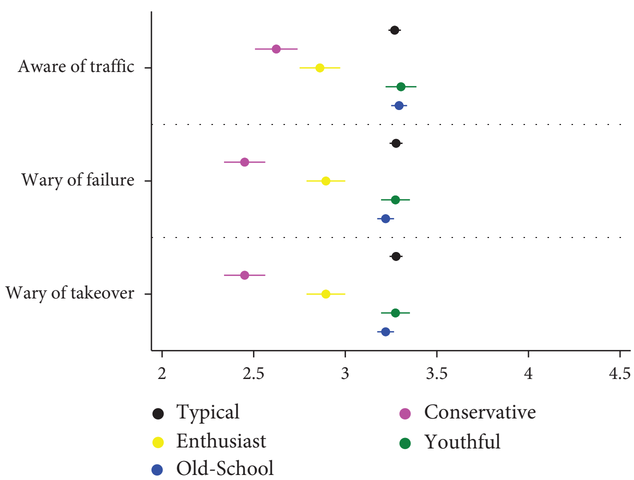

FIGURE 9: Mean values of attitudinal variables with 95% confidence interval by consumer classes. Measured items on the vertical axis: I think I would be more aware of the traffic environment in a CAC than when I would drive on my own; I would be concerned that a failure or malfunction of a CAC may cause accidents; I would be concerned to take over control of a CAC after being engaged in activities other than driving (e.g., watching a movie, using social media).

For the other attitudinal questions, the results are mixed (Figure 10). These questions relate to how respondents expect a CAC to "behave properly" (act appropriately, be reliable, present no safety concern, and behave predictably). Still, the conservative class scores are significantly lower than the other classes on all questions, except the question about monitoring the car.

Note that the above discussion is purely about correlation. We are not able to infer causality between these factors and the WTP measures (motorway, congested motorway, urban roads, parking areas). However, the above discussion may contribute to understanding what causes

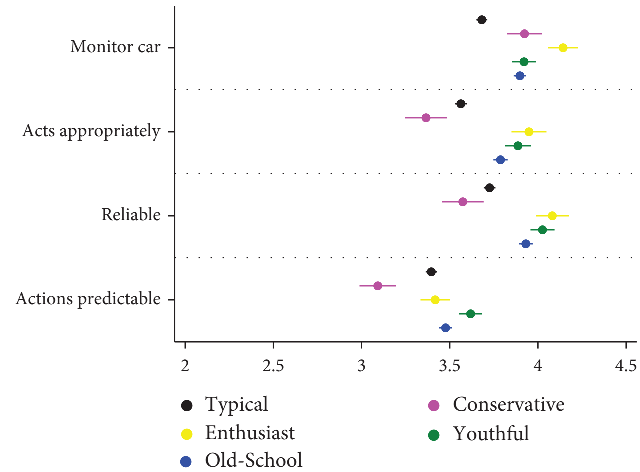

FIGURE 10: Mean values of attitudinal variables with 95% confidence interval by consumer classes. Measured items on the vertical axis: I think I would monitor the car's performance the whole time to be sure I can safely take over control of the car when needed; I would expect that a CAC would behave appropriately in all situations; I would expect a CAC to be reliable; I believe that the actions of a CAC would be predictable.

the reported differences in willingness to pay among the various classes of respondents. Furthermore, this may have important policy implications. As noted in the introduction, there are potentially great societal and private benefits from the increasing share of CACs [2]. Therefore, a sound understanding of which aspects of CAC usage cause respondents to worry about using this novel technology may aid in communicating benefits and costs to potential buyers of CACs. For instance, a pattern in the responses between the two low-WTP classes and the three high-WTP classes is that the classes differ when it comes to how the respondents expect to feel while using a CAC (comfortable, relaxed, safe), while for questions describing the driving environment (e.g., "acting appropriately," "being reliable," and "having predictable actions"), the results are more mixed.

4. Discussion

In this section, we discuss several interesting findings from the analyses related to generating classes of consumers or potential buyers of CACs and describe the classes in greater detail using demographic and attitudinal variables. The analyses rest on the latent constructs and latent profile analysis, where all except one latent construct were found to be consistent, while the latent construct "effort expectancy" was slightly lower than the desired level of internal consistency.

At one level, our results differ from those in the existing literature. For instance, the classes with the highest share of women have the highest average WTP for CACs, while the literature documents that females are more inclined to use and buy an automated vehicle [17]. The literature is not conclusive on the impact of age and attitudes toward automated driving [34], while Schoettle and Sivak [15] find that younger people demonstrate less concern about automated vehicles, and a greater likelihood of using them. A surprising result relates to age and young people's responses related to awareness of traffic, system failure, and taking over the driving. In our analysis, youthful respondents score higher than conservatives and enthusiasts, while Charness et al. [35] find that younger people are less concerned about automated vehicles than older people. Also, Ahmed et al. [36] find that younger people are less concerned about security threats due to hacker or terrorist attacks. Our results indicate that the class with the highest share of younger people has the lowest WTP for CACs. This may be explained by the fact that a large share of younger people is not in a financial position to pay extra for automated cars. In addition, our results are not directly comparable with other studies since our approach involves assigning individuals to classes. Additionally, the focus herein is on WTP for CACs, not their usage or intention to use them.

Based on our findings, we argue that the results both conform to and diverge from expectations. First, the conservative and youthful classes had a relatively low willingness to pay for CACs, which was as expected. The largest group, the typical class, had the highest WTP for CACs, which was also as expected. It is also good news for future market penetration of CACs that the largest classes have the highest WTP.

Furthermore, it is interesting to note that the conservative class has a high WTP for automated driving on motorways but a low WTP for urban roads and parking areas. One could speculate that conservatives are quite open to using automated driving functions in environments that are considered "easy" for ADFs but boring for human drivers. Moreover, it is interesting that the typical class has a high WTP for each ADF.

Consistent with previous studies (see [37] for an overview of these studies), we find a positive willingness to pay for novel automated driving technologies, in this case, conditionally automated cars. Our findings contribute to this literature by analyzing differences in willingness to pay among classes of consumers. Our analysis is also novel in that we study seven European countries, using representative samples of active car drivers in all these countries. We are not aware of any studies using our framework for estimating willingness to pay for automated driving by applying the UTAUT2-framework. In this respect, our study, represents a valuable contribution to the understanding of behavioral intentions related to CACs/automated driving.

The identification of CAC-consumer profiles provides insight into how policymakers could shape public policies to enhance the scope of CAC usage, enabling the benefits from these vehicles to be realized. For example, information campaigns could be directed toward classes of consumers who are expected to be early adopters of automated driving. Segmentation of potential buyers of CACs may also help car manufacturers identify obstacles to adoption and usage of CACs. This may be relevant for marketing and communication of CAC attributes and may guide pricing and advertising decisions.

5. Conclusion

The heterogeneity of a population was studied by identifying distinct classes of potential buyers of automated vehicles in Europe, utilizing a large survey from seven European countries. After dividing the population into five classes of consumers using latent profile analysis, the willingness to pay for conditionally automated cars for each class was assessed. In general, the majority of respondents were willing to pay for conditionally automated cars. Those with a relatively low willingness to pay were the conservative and youthful, while those with a relatively high willingness to pay for CACs were the typical, enthusiastic, and old-school classes of consumers. The observed differences in willingness to pay were related to demographic and attitudinal variables. In particular, the class with the lowest age was also the one with the lowest willingness to pay. Classes of consumers differed (or were related) along a range of attitudinal variables obtained from the survey. The conservative class scored low on attitudinal variables, while the enthusiastic class scored neutrally on these, whereas the other classes scored high. The youthful class scored high on attitudinal variables, but low on willingness to pay. Future research should pursue how various attitudes towards fully automated cars impact the willingness to pay for these vehicles.

The findings from this study provide important information on segments of potential buyers of higher-level automated vehicles, which would be useful for both vehicle manufacturers and public authorities in enabling the informed design of private and public information campaigns related to the new automated driving technology.

Appendix

A. Questions in UTAUT2-Framework

The questions asked for building the alternative latent constructs are given below. Response options were given on a 5-point Likert scale (strongly disagree to strongly agree).

Performance expectancy (PE):

(1) I expect that a conditionally automated car would be useful in meeting my daily mobility needs
(2) Using a conditionally automated car would help me reach my destination more safely
(3) Using a conditionally automated car would help me reach my destination more comfortably
(4) I assume that a conditionally automated car would be useful in my daily life

Effort expectancy (EF):

(1) Learning how to use a conditionally automated car would be easy for me
(2) I expect that a conditionally automated car would be easy to use
(3) It would be easy for me to become skillful at using a conditionally automated car

(4) I would recommend a conditionally automated car to others

Social influence (SI):

(1) I assume that people whose opinions I value would prefer that I use a conditionally automated car
(2) I expect that people who influence my behavior would think that I should use a conditionally automated car
(3) I expect that people who are important to me would think that I should use a conditionally automated car

Facilitating conditions (FC):

(1) I could acquire the necessary knowledge to use a conditionally automated car
(2) I would expect the use of a conditionally automated car to be compatible with other digital devices I use
(3) I would expect to have the necessary knowledge to use a conditionally automated car
(4) I would be able to get help from others when I have difficulties using a conditionally automated car

Hedonic motivation (HM):

(1) Using a conditionally automated car would be fun
(2) Using a conditionally automated car would be entertaining
(3) Using a conditionally automated car would be enjoyable

Behavioral intent (BI):

(1) I intend to use a conditionally automated car in the future
(2) Assuming that I had access to a conditionally automated car, I predict that I would use it
(3) I would use a conditionally automated car during my everyday trips
(4) I plan to buy a conditionally automated car once it is available

B. Attitudinal Items

Below are the items we refer to as attitudinal. Response options were given on a 5-point Likert scale (strongly disagree to strongly agree).

Please indicate to what extent you agree with the following statements, which relate to your expectations if you were using a conditionally automated car on driving function:

I would feel comfortable giving control to a conditionally automated car

I would feel comfortable giving control to a conditionally automated car

I would feel safe using a conditionally automated car

I would trust a conditionally automated car for my everyday travel

I think I would be more aware of the traffic environment in a conditionally automated car than when I would drive on my own

I would be concerned that a failure or malfunction of a conditionally automated car may cause accidents

I would be concerned to take over control from a conditionally automated car after being engaged in activities other than driving (e.g., watching a movie, using social media, etc.)

I think I would monitor the car's performance the whole time to be sure I can safely take over control from the car when needed

I would expect that a conditionally automated car would act appropriately in all situations

I would expect that a conditionally automated car would be reliable

I believe that the actions of a conditionally automated car would be predictable

Data Availability

The data used to support the findings of this study are currently under embargo because of ongoing parallel studies.

Disclosure

The information and views set out in this paper are those of the authors and do not necessarily reflect the official opinion of the European Commission.

Conflicts of Interest

The authors declare that they have no conflicts of interest to disclose.

Acknowledgments

The research in this study received funding from the European Commission Horizon 2020 program under the project L3Pilot (grant agreement no. 723051).

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