# Consumer Intentions for Alternative Fuelled and Autonomous Vehicles: A segmentation analysis across six countries

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## Abstract

Rapid advances in the development of autonomous and alternative-fuelled vehicles (AFVs) are likely to transform the future of mobility and could bring benefits such as improved road safety and lower emissions. Achieving these potential benefits requires widespread consumer support for these disruptive technologies. To date, research to explore consumer perceptions of transport innovations has tended to consider them in isolation (e.g., driverless cars, electric vehicles). The current paper examines the predictors of consumer interest in and willing to pay for both cleaner and autonomous vehicles through a choice experiment conducted in six diverse markets: Germany, India, Japan, Sweden, UK and US. Using Latent Class Discrete Choice Models, we observe significant heterogeneity both within and across the country samples. For example, while Japanese consumers are generally willing to pay for autonomous vehicles, in most European countries, consumers need to be compensated for automation. Within countries, though, we found some segments – typically, more educated, innovative, and self-identifying as green – are more in favour of automation. Significantly, we also found that support for autonomous vehicles is associated with support for AFVs, perhaps, due to common demographic or socio-psychological predictors of both types of innovative technology. These findings are valuable for policymakers and the automotive industry in identifying potential early adopters as well as consumer segments or cultures less convinced to these innovative transport technologies.

## Keywords

alternative-fuelled vehicles; autonomous vehicles; car choice; discrete choice experiment; segmentation

## 1. Introduction

The automotive sector is seeing significant change due to shifting consumer demands, technological innovation, and transport policies to tackle air pollution, climate change, accidents and congestion. Rapid advances in the development of autonomous and alternative-fuelled vehicles, in particular, are likely to transform the future of mobility (Whittle et al., 2019). Anticipated benefits of autonomous vehicles (AVs) include the possibility to engage in work and leisure activities whilst being transported, enhanced mobility for those unable to drive, and improved road safety; while alternative-fuelled vehicles (AFVs; including electric, hybrid and biofuel) are expected to improve urban air quality and reduce carbon emissions (GOS, 2019). The market for driverless cars is projected to be $7 trillion by 2050 (Lanctot, 2017) and within 7-10 years, 30% of vehicles are expected to be electric and autonomous (NLR, 2019). However, achieving these goals requires widespread consumer support for these disruptive technologies, and there remain significant consumer concerns about both AVs and AFVs (Whittle et al., 2019). To date, though, research to explore consumer perceptions of novel transport technologies has tended to consider them in isolation (e.g., driverless cars, electric vehicles). The current paper examines the predictors of consumer interest in and willing to pay for both cleaner and autonomous vehicles across diverse global markets.

Advanced driver assistance systems, such as lane correction or adaptive cruise control system, assist the driver in their usual driving behaviour and overall transport decisions. However, through taking away the need to always be in manual control of the vehicle, autonomous (or self-driving) vehicles have the potential to disrupt both usual driving behaviours and overall transport decisions (Krueger et al., 2016). The Society of Automotive Engineers (SAE International, 2018) defines six levels of automation from Level 0 (no automation) to Level 5 (full automation). Levels 1 and 2 represent the advanced driver assistance systems that are already included in certain vehicles. However, Level 3 and especially Levels 4 and 5 represent a shift into the greater automation of driving, with the capabilities of the automotive system increasing at each level. Simplified descriptions for each level are shown in Table 1. Studies on the public acceptance of autonomous vehicles have typically investigated vehicles with Level 4 or 5 automation (Gkartzonikas and Gkritza, 2019).

**Table 1. Levels of automation (Source: SAE International, 2018)**

| Level | Name | Description |
|---|---|---|
| 0 | No driving automation | Zero autonomy; the driver performs all driving tasks. |
| 1 | Driver assistance | Vehicle is controlled by the driver, but some driving assist features may be included in the vehicle design. |
| 2 | Partial driving automation | Vehicle has combined automated functions, like acceleration and steering, but the driver must remain engaged with the driving task and monitor the environment at all times. |
| 3 | Conditional driving automation | Driver is a necessity but is not require to monitor the environment. The driver must be ready take control of the vehicle at all times, without notice. |
| 4 | High driving automation | The vehicle is capable of performing all driving functions under certain conditions. The driver may have the option to control the vehicle. |
| 5 | Full driving automation | The vehicle is capable of performing all driving functions under all conditions. The driver may have the option to control the vehicle. |

Although there is consumer interest in the anticipated benefits of autonomous vehicles, such as the possibility to engage in work and leisure activities whilst being transported; opportunities for those unable to drive or the potential safety benefits (Howard and Dai, 2014; Le Vine et al., 2015), general attitudes towards AVs are mixed and differences between countries have been observed. For instance, in one study, Australia had the highest percentage of positive opinions (61.9% of 505), the US second highest (56.3% of 501) and the UK third (52.2% of 527) (Schoettle and Sivak, 2014). An analysis of the 2014 Eurobarometer data found that in all countries of the European Union (except Poland), participants felt “uncomfortable” about autonomous cars. Again, there were differences between the countries: for example, while only 35% of respondents in Poland and 48% in Sweden felt “totally uncomfortable” about travelling in an AV, this rose to 67% in Germany and 77% in Cyprus (Hudson et al., 2019). More recently, a cross-national survey (Continental, 2018) of around 1,000 consumers in each country found that more respondents in China and Japan (89%

and 68%, respectively) viewed automated driving as a sensible advancement compared to in Germany and the US (53% and 50%, respectively). These studies highlight the potential for cross-national differences in attitudes towards AVs.

The cost of AVs, relative to traditional cars, has been found to be a concern in public surveys (Clark et al., 2016; Haboucha et al., 2017). Indeed, Schoettle and Sivak (2014) found that in a survey of US, UK and Australian public, there was a desire in the majority of respondents to have automation, however, a majority was also unwilling to pay extra to have it. However, whilst cost is perceived as a barrier to AV adoption (Howard and Dai, 2014), studies have found a range of willingness to pay (WTP) values. Compared to conventional vehicles, Jiang et al. (2018) found that Japanese respondents were willing to pay between US$3557-$7019 for level 3, 4 and 5 AVs, with higher levels of automation corresponding to the higher WTP. In the US, Bansal et al. (2016) found a WTP for AVs between US$3300 (for Level 3) and US$7253 (for Level 4). Slightly lower values of US $3500 (for partial automation) and US$4900 (full automation) were found in the US by Daziano et al. (2017). The authors also note the heterogeneity in their sample's WTP, however, with some participants' willing to pay over US$10,000 and others not willing to pay any extra.

The WTP for autonomous vehicles has been found to have a positive relationship with income in the US (Bansal et al., 2016), China (Liu et al., 2019), and on average across multiple countries (Kyriakidis et al., 2015). However, income itself did not have a significant effect on intention to use the automation technology in either Bansal et al. (2016) or Kyriakidis et al. (2015). Further factors found to positively relate to WTP include higher number of vehicle miles travelled and current vehicle possessing cruise control (Kyriakidis et al., 2015), being male (Bansal et al., 2016; Kyriakidis et al., 2015), a higher number of past crashes (Bansal et al., 2016), and perceived benefits (Liu et al., 2019). Factors found to be negatively related to WTP included age (Bansal et al., 2016; Liu et al., 2019) and perceived risk and dread (Liu et al., 2019). More broadly, acceptance of AVs has been negatively related to concerns of safety (for drivers and passengers) and threats to privacy (hackers and data sharing) (Bansal et al., 2016; Kyriakidis et al., 2015; Schoettle and Sivak, 2014). Likewise, finding pleasure in driving, and valuing a car for luxury, image and prestige have each been found to relate to an unwillingness to relinquish driving control to autonomous systems (Howard and Dai, 2014). In line with this, intentions to use an AV have been found to decrease with higher levels of automation (Rödel et al., 2014). Finally, environmental concern – whilst positively associated with choosing shared autonomous vehicles – has been associated with a lower probability of choosing private autonomous vehicles (Lavieri et al., 2017). Similarly, current more sustainable transport behaviour was positively associated with intentions to use shared autonomous vehicles, but not intentions to own an autonomous vehicle (Lavieri et al., 2017). The present study contributes to this literature by exploring socio-demographic factors and environmental identity in relation to distinct levels of vehicle autonomy.

This paper extends the literature on autonomous vehicles by providing insight about individual consumer preferences regarding autonomous cars in the context of other vehicle attributes, including alternative fuels. Previous research indicates environmental considerations generally exert little salience in product choice, whereas economic, pragmatic and social factors are typically more influential (e.g. Haggar and Whitmarsh, 2017). Car choice reflects both demographic and situational factors, as well as personality or lifestyle factors. For example, large car ownership is linked to higher income, but also to valuing personal status; small car ownership is associated with high-density urban living, but also to being environmentally oriented (Choo and Mokhtarian (2004). Preferences for AFVs have similarly been linked to both demographic (e.g., income) and socio-psychological predictors, such as pro-environmental identity, status seeking and being an early adopter of new technology (Rezvani et al., 2015). For example, Barbarossa et al. (2015) found that intention to buy eco-friendly electric cars was associated with 'green' self-identity in Danish, Belgian and Italian samples. Elsewhere, Noppers et al. (2015) found that self-identified early adopters more often intended to purchase EVs compared to those identifying as late adopters. Social norms and cultural values also appear to influence preferences for AFVs (Pettifor et al., 2017), highlighting the need for further cross-national studies.

In this study, we integrate these largely distinct literatures on adoption of AVs and AFVs in a cross-national choice experiment. The aim study was to examine the demographic and socio-psychological predictors of consumer interest in and willing to pay for both cleaner and autonomous vehicles across six diverse countries: Germany, India, Japan, Sweden, UK and US. It is interesting to compare consumers' car-purchase intentions across these countries as they reflect a diverse range of cultural orientation, including individualism, with the UK and US considered to be highly individualistic, Germany and Sweden moderately individualistic and India and Japan being collectivist and less individualistic (Hofstede, 1980). Furthermore, these countries reflect major and growing markets for consumer products, so are important contexts in which to explore preferences for and potential adoption of new technologies. To our knowledge, the present study is the first to examine how consumer segments differ in their preferences for autonomous driving in the context of different car types including alternative fuel vehicles.

## 2. Materials and Methods

### *2.1 Stated choice experiment and survey*

The survey comprised a car choice discrete choice experiment (DCE), which was designed to examine whether consumers placed any importance on and estimate WTP for autonomous driving in the context of alternative-fuelled vehicles being potential options with diverse attributes. The choice setting in the DCE assumed individual rather than household choices as the aim of the study was to explore links across (individual) intentions to purchase a car, socio-economic and psychological predictors in line with studies mentioned in the previous section. Each participant was presented with five choice tasks and was asked to choose from a petrol, electric, biofuel and hybrid car option. As shown in Figure 1, each car option was described by eight attributes with levels varying according to a D-efficient experimental design based on the multinomial logit model (MNL) and prior parameters set equal to zero (Hensher et al., 2015)[1]. Sixty (60) choice cards were generated using the software Ngene and incorporated a blocking algorithm to reduce the choice cards to a feasible number (five) for each participant (ChoiceMetrics, 2010).

Targeted reviews of the literature on factors influencing car choice informed the design a vehicle-type choice discrete choice experiment and the selection of attributes and

[1] Experimental designs are aimed at deriving a reduced set of attribute combinations, to create 'packages' of alternative vehicle options as shown in Figure 1. While these options can be derived by randomly sampling attribute levels, experimental designs follow a systematic approach aimed at minimising correlation between attributes (fractional factorial designs) or minimising the standard errors of the estimated parameters (efficient designs). D-efficient designs are the most widely used approach to generate an experimental design matrix (see, Hensher et al., 2015; ChoiceMetrics, 2010).

their levels, in particular (Haggar and Whitmarsh, 2017; Whittle et al., 2019). Feedback on preliminary sets of attributes was sought through 10 qualitative interviews with a UK-based convenience sample. The selected attributes, which were used to describe each car option, aimed at covering both functional and symbolic/affective attributes known to be significant for car choice (Haggar and Whitmarsh, 2017; Potoglou and Kanaroglou, 2007, 2008) such as price and running cost, functionality/practicality (size, fuel availability, acceleration), environmental credentials (fuel type, materials), and design, as well as the autonomous driving capability of each car option (see, Table 2). To aid comparison, the running cost amounts were kept uniform across the alternative fuels and calculated as percentages of the running costs of petrol vehicles. As the estimations for the long-term running costs of AFVs are varied, a more conservative 60% saving was chosen as the lower percentage and a 90% saving chosen as the upper percentage.

Vehicle size was specified as the carrying capacity (internal room size) of the car in terms of the number of seats and suitcases rather than its shape (e.g. mini-van, SUV or pick-up). While this was a simplified specification relatively to the available vehicle types, it was cognitively easier for respondents and allowed for adequate variability over the alternatives to be able to conduct cross-country comparisons.

“*Thinking about your next car purchase, which car out of the following options would you choose?”*

| | Petrol | Electric | Biofuel | Hybrid |
|---|---|---|---|---|
| **Price ($)** | 35,000 | 49,000 | 45,500 | 35,000 |
| **Size** | Large | Mid-size | Mid-size | Large |
| **Autonomous driving** | Driver assistance | High automation | Driver assistance | Partial Automation |
| **Annual running cost ($)** | 985.00 | 788.00 | 886.50 | 886.50 |
| **Availability of fuel at existing petrol stations (%)** | 100 | 60 | 60 | 100 |
| **Materials** | Conventional materials | Conventional materials which are climate neutral | Conventional materials, which are climate neutral | Organic materials |
| **Design** | Conventional design | Conventional design | Conventional design | Conventional design |
| **Acceleration (0-60 mph in seconds)** | 8 | 12 | 12 | 6 |

Figure 1. An example choice card of the car choice experiment

**Table 2. Attributes and levels in the car-choice experiment**

| Attribute | [Level] Description |
|---|---|
| Materials | [1]. Conventional materials (base level)<br>[2]. Conventional materials, which are ethically-sourced<br>[3]. Conventional materials, which are climate-neutral<br>[4]. Organic materials<br>[5]. Organic materials, which are climate-neutral<br>[6]. Organic materials, which are ethically-sourced |
| Exterior design in terms of the car's shape, colour and style | [1]. Conventional design (base level)<br>[2]. Unique design |

| Attribute | [Level] Description |
|---|---|
| Annual running cost* | [1]. Average cost of a present-day petrol car for 10,000 kms<br>[2]. 60% of a present-day petrol car<br>[3]. 70% of a present-day petrol car<br>[4]. 80% of a present-day petrol car<br>[5]. 90% of a present-day petrol car |
| Availability of fuel at existing petrol stations (%)* | [1]. 40% of existing petrol stations<br>[2]. 60% of existing petrol stations<br>[3]. 80% of existing petrol stations<br>[4]. 100% of existing petrol stations (base level) |
| Acceleration: 0 to 60 mph/100kph in seconds | [1]. 6<br>[2]. 8<br>[3]. 10<br>[4]. 12 |
| Level of autonomous driving | [1]. Level 0 - Zero automation (base level)<br>[2]. Level 1 - Driver assistance<br>[3]. Level 2 - Partial assistance<br>[4]. Level 3 - Conditional automation<br>[5]. Level 4 - High automation<br>[6]. Level 5 - Full automation |
| Size | [1]. Small (4 seats, 3 doors, 2 suitcases) (base level)<br>[2]. Mid-size (5 seats, 5 doors, 4 suitcases)<br>[3]. Large (5 seats, 5 doors, 6 suitcases) |
| Price | [1]. Amount respondents would pay upfront (base level)<br>[2]. 20% higher than the base level<br>[3]. 30% higher than the base level<br>[4]. 40% higher than the base level |

* Only applicable in the biofuel and electric car options

Participants were provided with definitions of all the attributes and their levels used in the experiment, including the 0-5 levels of autonomous driving (see, Table 1). To enhance the realism of the experiments, participants answered background questions relating to purchase intentions to buy a car including the money they would spend to purchase a car. The latter allowed us to vary prices relative to the amount participants said they would be likely to spend on purchasing a car. Prior to the main survey, we undertook a further 10 cognitive interviews with a UK-based convenience sample to ensure terminology used in the stated-choice tasks was understandable and further refine the levels of the selected attributes (see, Section 2.3).

Respondents were made aware that all other car features (attributes) of their (purchase) choice would be ‘satisfactory to you’. Such features included colour, manufacturer/brand of the car, and its mileage in the case of second-hand cars. Previous studies, driven primarily by their scope and research objectives, have also introduced an array of other attributes such as trip range and charging time – especially, in the case of electric cars, the potential proportion of reduced emissions – in the case of hybrid-electric cars or cars powered by biofuel, and government subsidies. These were beyond the scope of this study which aimed consumer preferences (and their heterogeneity) for autonomous driving levels including alternative fuelled car options. The selected attributes for this experiment presented a sufficient number and type for respondents to trade-off and make choices across car alternatives of the experiment within a realistic setting; the latter was also confirmed through cognitive interviews (see also, Section 2.3).

### *2.2 Additional survey measures*

Following the choice experiment, socio-psychological questions, including pro-environmental identity, innovativeness and knowledge, were asked, along with demographic items (see Appendix A).

- *Pro-environmental identity*: Whitmarsh and O'Neill (2010) widely used the measure of green identity. This includes four items (see, Appendix for all items and descriptive statistics), e.g., 'I think of myself as an environmentally-friendly person', 'I would not want my family or friends to think of me as someone who is concerned about environmental issues' (reverse coded) on a five-point response scale from strongly disagree (1) to strongly agree (5). Items were scaled to form a single measure of green identity ($\alpha_{UK}(4)=.62$; $\alpha_{US}(4)=.63$; $\alpha_{Sweden}(4)=.50$; $\alpha_{Germany}(4)=.55$; $\alpha_{Japan}(4)=.53$; $\alpha_{India}(4)=.44$).
- *Innovativeness*: Noppers et al's (2015) measure to identify car adopter segments was used. Respondents were asked to indicate which statement most closely described them (preceded by 'I am the type of person who…'): 'Closely follow new technological developments and who dares taking risks by being the first to purchase an innovative car' to 'Is traditional and has little affinity with innovative car; I do not like changes in life and I purchase an innovative car only when the existing model I use is not produced anymore' (see Appendix B for all items).
- *Knowledge*. Another question elicited respondents' knowledge about sustainable materials in cars, respectively: 'How much do you know about the sustainability of the materials that cars are made from' with a 10-point response scale from 1 (Nothing at all) to 10 (A great deal).

### *2.3 Survey implementation*

The choice experiment was pre-tested using cognitive interviews (Padilla and Leighton, 2017). Ten participants (8 females, 2 males) were recruited through convenience sampling (mean age of 31.) All worked for a university or were currently an undergraduate student. Six owned cars and drove regularly. Four did not own cars, of which three intended to own one in the future. The cognitive interviews confirmed that the attributes could be meaningfully compared and traded-off by participants. Fuel type strongly influenced choice, as did fuel availability and not wanting high levels of autonomous capabilities. Critically, participants were uncertain whether the autonomous features could be turned off and the car driven manually as it was not specified in the pre-test explanation of the automation levels. As it is anticipated that a vehicle equipped with Level 4 or Level 5 automated driving systems (ADS) might be designed without user interfaces operable by a conventional, human driver (i.e., a driverless vehicle) (SAE International, 2018), it was subsequently specified that the Level 5 automation could not be turned off and the vehicle could not be driven manually (although the vehicle could be directed). For automation Levels 0-4 it was specified that autonomous capabilities could be turned off and the vehicle driven conventionally. This distinction also allowed for the exploration of the importance of being able to manually control the vehicle or not, an aspect highlighted in AV acceptance literature as being influential (Howard and Dai, 2014).

The choice experiment and survey were translated from English to Swedish, German, Hindi and Japanese, and the translations were checked by native speakers and were revised as appropriate. The choice experiment was then embedded in the Qualtrics survey software, along with the other survey items. Following internal survey checks, we 'soft launched' the survey with 50 respondents in each of the six countries, to further check data quality, prior to launching the main survey. All responses were time tracked and those who were completed in less than seven (7) minutes were more likely to be insincere answers or did not take the survey seriously, given the length of the survey questionnaire. We also made a visual inspection of all responses and screened out 'flatliners' and other dubious respondents. These responses were discarded from the sample and were replaced by new responses.

Participants were recruited via the Qualtrics online panel (https://www.qualtrics.com) and data were collected in October 2018. A quota sample of around 1,000 consumers per country was recruited to provide a representative national sample matched on age (18 years or older), gender and region of each country based on census data. The median of the total completion time of the survey was consistent across countries ranging from 12.8 minutes in Japan to a maximum of 15.7 minutes in India and the US[2].

A total sample of 6,033 respondents across the six countries participated in the study. Participant details are shown in Table 3. Given the specification of corresponding quotas prior of data collection, the data were consistent with census data across age, gender and geographic area of residences. For example, the Indian sample included younger individuals compared than the other samples. On the other hand, the Indian and the US samples had the highest proportions of respondents with higher education qualifications – i.e., 52%-54% had a university degree. The Indian sample is far from providing a representative profile of the general population other than age, gender and geographic area of residence. For example, in terms of education approximately 46% of 25-64-year olds in the population have no primary education (OECD, 2017). In terms of income, Indian respondents below the median income were underrepresented given the observed proportions in the sample.

**Table 3. Sample characteristics**

| | Number of respondents (%) | | | | | |
|---|---|---|---|---|---|---|
| | Germany | India | Japan | Sweden | UK | US |
| **Gender** | | | | | | |
| Females | 518 (51.2) | 526 (47.6) | 544 (53.5) | 495 (50.0) | 498 (54.3) | 514 (51.4) |
| Males | 494 (48.8) | 579 (52.4) | 471 (46.4) | 494 (49.9) | 418 (45.6) | 484 (48.5) |
| Prefer not to say | - | 1 (0.1) | 1 (0.1) | 1 (0.1) | 1 (0.1) | 1 (0.1) |
| **Age (years)** | | | | | | |
| 18 – 24 | 118 (11.6) | 281 (25.4) | 104 (10.2) | 115 (11.6) | 122 (13.3) | 121 (12.1) |
| 25 – 34 | 166 (16.4) | 327 (29.6) | 150 (14.7) | 193 (19.5) | 162 (17.6) | 179 (17.9) |
| 35 – 44 | 189 (18.7) | 241 (21.8) | 201 (19.8) | 164 (16.6) | 164 (17.9) | 163 (16.3) |
| 45 – 54 | 207 (20.5) | 152 (13.7) | 197 (19.4) | 172 (17.4) | 187 (20.4) | 174 (17.4) |
| 55 – 64 | 175 (17.3) | 74 (6.7) | 180 (17.7) | 165 (16.6) | 151 (16.5) | 168 (16.8) |
| 65+ | 157 (15.5) | 31 (2.8) | 184 (18.1) | 181 (18.3) | 131 (14.3) | 194 (19.4) |
| Prefer not to say | - | - | 1 (0.1) | - | - | - |
| **Education qualifications** | | | | | | |

[2] Total completion times (minutes):
- Mean: Germany: 18.3; India: 19.3; Japan: 17.6, Sweden: 22.7, UK: 12.7, US: 22.2
- Median: Germany: 15.3; India: 15.7; Japan: 12.8, Sweden: 15.4, UK: 15, US: 15.7

| | Number of respondents (%) | | | | | |
|---|---|---|---|---|---|---|
| | Germany | India | Japan | Sweden | UK | US |
| Lower than university degree | 714 (71.0) | 494 (44.7) | 602 (59.7) | 644 (65.0) | 607 (66.6) | 483 (48.3) |
| University degree or higher | 291 (29.0) | 601 (54.3) | 406 (40.2) | 345 (34.9) | 305 (33.4) | 516 (51.7) |
| Prefer not to say | - | 11 (1) | 1 (0.1) | 1 (0.1) | - | - |
| **Have Children** | | | | | | |
| Yes | 556 (55.0) | 633 (57.2) | 517 (51.9) | 589 (59.5) | 542 (59.1) | 573 (57.4) |
| No | 441 (43.6) | 456 (41.2) | 478 (47.9) | 386 (39.0) | 365 (39.8) | 412 (41.2) |
| Prefer not to say | 15 (1.4) | 17 (1.6) | 14 (1.4) | 15 (1.5) | 10 (1.0) | 14 (1.4) |
| **Annual Household Income** | | | | | | |
| Below median income | 338 (33.4) | 210 (19.0) | 475 (46.7) | 377 (38.1) | 335 (36.5) | 380 (38.4) |
| Median income or higher | 665 (65.7) | 896 (81.0) | 537 (52.8) | 606 (61.2) | 541 (59.0) | 616 (61.6) |
| Prefer not to say | 9 (0.9) | - | 5 (0.5) | 7 (0.7) | 41(4.5) | 3 (0.3) |
| **Total** | **1,012** | **1,106** | **1,009** | **990** | **917** | **999** |

## 3. Analytical approach

The stated choice data involving different fuel technologies and levels of automation were analysed by estimating a latent class model (LCM) for each country. The primary scope of LCM – and continuous mixture (mixed) logit models – is to capture the unobserved (random) heterogeneity across individuals. On the other hand, a purely deterministic account of heterogeneity – for example, using interactions within a multinomial logit (MNL) modelling framework, could lead to loss of explanatory power and potential bias in key model outputs (see, Hess, 2014). Unlike the MNL, which treats each individual response as independent (i.e., the five choices provided by each respondent are treated as independent observations) and is restricted by the Independence of Irrelevant Alternatives (IIA) property, discrete (LCM) or continuous mixture models can account for serial correlation thus controlling for the panel nature of the choice data and relax IIA. Greene and Hensher (2003) and Hess (2014) provide a theoretical and practical discussion of the differences of these models, respectively.

LCMs account for unobserved taste heterogeneity in choices across respondents by grouping them into different (latent) classes and estimating different parameters for each class; although the class allocation is unknown to the analyst (Train, 2009). Unlike continuous mixture discrete choice models, LCMs do not rely on simulation and require fewer assumptions (e.g. forcing model parameters to follow a specific choice distribution) thus reducing the risk of obtaining biased results (Greene and Hensher, 2003). Under the Random Utility Theory, an individual $n$ who belongs in class $c$ assigns a utility $U$ for car option $i$ ($i$ = petrol, hybrid, electric or biofuel) in choice card $t$, which is mathematically described as:

$$U_{int|c} = \boldsymbol{x}'_{int} * \boldsymbol{\beta}_c + \varepsilon_{int|c} \qquad [1]$$

where
$\boldsymbol{x}$ corresponds to the vector of car attributes in the choice experiment (see, Table 2) including an alternative specific constant $\mathbf{a_i}$; $\boldsymbol{\beta_c}$ are class-specific parameters of car attributes to be estimated and $\varepsilon$ is the unobserved component of the utility (error term).

For an individual respondent $n$ who belongs to class $c$, the probability of choosing car option $i$ from a set of $I_n$ alternatives would take the form of a multinomial logit model (MNL) (Greene and Hensher, 2003; Pacifico and Yoo, 2013):

$$Prob[car\ i\ by\ individual\ n\ in\ choice\ situation\ t|class\ c] = \frac{\exp(\boldsymbol{x'}_{int}\boldsymbol{\beta}_c)}{\sum_{j=1}^{I_n}\exp(\boldsymbol{x'}_{jnt}\boldsymbol{\beta}_c)} \quad [2]$$

Equation 3 shows that for a sample of *N* respondents the probability of making a sequence of choices $\boldsymbol{y_n}$ is the product of MNL formulas over the total of $T_n$ choice tasks and number of alternatives $I_n$ conditional on the class $c$ (Pacifico and Yoo, 2013):

$$P_{n|c}(\beta_c) = \prod_{t=1}^{T_n}\prod_{i=1}^{I_n}\left\{\frac{exp(\boldsymbol{x'}_{int}\boldsymbol{\beta}_c)}{\sum_{i=1}^{I_n}\exp(\boldsymbol{x'}_{int}\boldsymbol{\beta}_c)}\right\}^{y_{int}} \quad [3]$$

The allocation of respondents to a class $c$ can be estimated based on individual characteristics, $\boldsymbol{z}_n$ and class specific constants $\delta_c$. This is the key flexibility of this model structure as it allows to link the probability of a respondents allocated in a class with socio-demographic characteristics of the respondent such as age and gender and socio-psychological predictors (Hess, 2014). Using the multinomial logit formulation, the expression for this probability conditioned by individual covariates can be expressed by (Greene and Hensher, 2003; Hess, 2014; Pacifico and Yoo, 2013):

$$p_{nc(\boldsymbol{\theta})} = \frac{\exp(\delta_c + \boldsymbol{z}_n'\boldsymbol{\theta}_c)}{\sum_{c=1}^{C}\exp(\delta_c + \boldsymbol{z}_n'\boldsymbol{\theta}_c)},\ c = 1, \ldots, C\ with\ \ \boldsymbol{\theta}_C = \boldsymbol{0}\ and\ 0 \leq p_{nc(\boldsymbol{\theta})} \leq 1 \quad [4]$$

The vector $\boldsymbol{\theta}_C$ is normalized to zero for identification (Greene and Hensher, 2003; Pacifico and Yoo, 2013).

The log-likelihood function for the sample is the sum of each respondent's natural logarithm of the unconditional likelihood (Pacifico and Yoo, 2013):

$$lnL\ (\boldsymbol{\beta}, \boldsymbol{\theta}) = \sum_{\mathrm{n=1}}^{\mathrm{N}} \ln\left[\sum_{c=1}^{C} p_{nc(\theta)} P_{n|c}(\beta_c)\right] \quad [5]$$

An LCM comprised a total set of $C$ classes will result in estimating $\boldsymbol{\beta} = (\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \ldots, \boldsymbol{\beta_C})$ taste parameters and the only parameter of the model to be set by the analyst is the number of classes $C$. There are several likelihood-based tests or Information Criteria (IC) that help analyse the best number of classes, including the Akaike information criterion (AIC) and the Bayesian Information Criterion (BIC). The estimation of the LCM specifications in this study were conducted using STATA's `lclogit` (Pacifico and Yoo, 2013) and `lclogit2` (Yoo, 2019) commands.

For each class *c*, the marginal WTP for different autonomous driving levels is computed as the ratio of the marginal utility of an autonomous driving level over the purchase price coefficient:

$$Marginal\ WTP_{autonomous\ driving,C} = -\frac{\beta_{autonomous\ driving\ level,c}}{\beta_{price,c}} \quad [6]$$

Confidence intervals for the marginal WTP values are estimated with the Delta Method using the `wtp` command in STATA 13 (Hole, 2007).

## 4. Results

Diagnostic questions following the choice experiments showed that participants felt able to make comparisons across the different car options, except for an average 3.5%

of each sample across the six countries. Observations from respondents who indicated they were unable to make comparison were screened out from further analysis. Also, prior to the estimation of the LCMs for each country, the data were analysed for missing data[3] and non-trading[4] behaviour – i.e., respondents who consistently chose the same alternative across the five choice cards (Hess et al., 2010). Further analyses showed that although the proportions of non-traders were high across countries, these were genuine responses as more than 90% of non-traders always selected the petrol option, which was the dominant car fuel type across all the countries in this study. We opted to exclude these responses from further analysis, however, the characteristics of respondents in the remaining sample were not significantly different from the total sample, except from income across all countries and the proportion of those with university degree in the US (see, Supplementary File 1).

As mentioned in Section 3, the first step in the analysis involved an iterative model estimation in order to determine the number of classes that best capture the unobserved heterogeneity in the car-choice data. We tested LCMs having 2 – 4 classes and assessed these against objective model-fit criteria such as the Akaike Information Criterion (AIC), Rho-Square and the Bayesian Information Criterion (Greene and Hensher, 2003; Hess, 2014). Other criteria revolved around: the ability to interpret the model estimations (e.g. challenging in the case of more than four classes), derive estimations with non-significant estimates of purchase price, exclude small classes (<5% of the sample) and provide a relatively similar number of classes that would be easy to contrast across countries (see, Axsen et al., 2015). The optimal solution was to estimate two-class models, as these models had the lowest BIC – which penalises more heavily for extra parameters (Train, 2009; p.368), across countries except Sweden (see, Table 4), and the other criteria mentioned above.

**Table 4. Latent-class model characteristics and fit measures for 2-4 classes**

| Nr. of classes | Model characteristics | Germany | India | Japan | Sweden | UK | US |
|---|---|---|---|---|---|---|---|
| 1 | Nr. of parameters (k) | 20 | 20 | 20 | 20 | 20 | 20 |
| (MNL) | Log-likelihood (LL) | -2977 | -3552 | -2474 | -3318 | -3313 | -3415 |
| | AIC[a] | 5994 | 7144 | 4988 | 6676 | 6666 | 6870 |
| | BIC[b] | 6109 | 7262 | 5100 | 6792 | 6783 | 6988 |
| | $Rho^2$ [c] | 0.07 | 0.03 | 0.09 | 0.03 | 0.06 | 0.09 |
| | Adjusted-$Rho^2$ [d] | 0.06 | 0.03 | 0.08 | 0.03 | 0.06 | 0.09 |
| 2 | Nr. of parameters (k) | 49 | 48 | 49 | 49 | 49 | 49 |
| | Log-likelihood (LL) | -2831 | -3468 | -2372 | -3170 | -3144 | -3283 |
| | AIC | 5760 | 7031 | 4843 | 6439 | 6386 | 6664 |
| | BIC | 5963 | 7237 | 5037 | 6645 | 6593 | 6875 |
| | $Rho^2$ | 0.12 | 0.06 | 0.12 | 0.07 | 0.11 | 0.13 |
| | Adjusted-$Rho^2$ | 0.10 | 0.04 | 0.11 | 0.06 | 0.09 | 0.11 |
| 3 | Nr. of parameters (k) | 78 | 76 | 78 | 78 | 78 | 78 |
| | Log-likelihood (LL) | -2753 | -3394 | -2328 | -3076 | -3057 | -3205 |
| | AIC | 5663 | 6940 | 4811 | 6308 | 6270 | 6567 |
| | BIC | 5986 | 7264 | 5121 | 6636 | 6600 | 6902 |
| | Rho2 | 0.14 | 0.08 | 0.14 | 0.10 | 0.13 | 0.15 |
| | Adjusted-Rho2 | 0.12 | 0.06 | 0.11 | 0.08 | 0.11 | 0.13 |
| 4 | Nr. of parameters (k) | 107 | 104 | 107 | 107 | 107 | 107 |
| | Log-likelihood (LL) | -2692 | -3357 | - 2277 | -3020 | -2998 | -3163 |
| | AIC | 5598 | 6921 | 4767 | 6253 | 6209 | 6539 |

[3] Missing data – Mean: 3.5%; Min: 1% in India; Max.: 5.5% in Japan

[4] Non-trading – Mean 36.3%; Min: 30.8% in the UK; Max: 45% in Japan

| Nr. of classes | Model characteristics | Germany | India | Japan | Sweden | UK | US |
|---|---|---|---|---|---|---|---|
| | BIC | 6041 | 7366 | 5192 | 6703 | 6662 | 6999 |
| | Rho2 | 0.16 | 0.09 | 0.16 | 0.12 | 0.15 | 0.16 |
| | Adjusted-Rho2 | 0.13 | 0.06 | 0.12 | 0.09 | 0.12 | 0.13 |
| Nr. of cases | | 9240 | 10620 | 7820 | 9880 | 10180 | 10840 |
| Nr. of observations[5] (N) | | 2310 | 2655 | 1955 | 2470 | 2545 | 2710 |
| Nr. of individuals | | 462 | 531 | 391 | 494 | 509 | 542 |
| LL(0) | | -3202 | -3681 | -2710 | -3424 | -3528 | -3757 |

[a] Akaike Information Criterion = -2*(LL-k)
[b] Bayesian Information Criterion = -2LL + k ln(N)]
[c]$Rho^2$=1 – (LL/LL(0) with LL(0): Log-likelihood with all parameters at zero
[d]Adjuested-$Rho^2$ = 1 - (LL(model)-k/LL(0))

Tables 5 and 6 present the estimated coefficients of two-class LCMs and the coefficients of individual characteristics and psychometric scales explaining the probability of a respondent belonging in a particular class, respectively. The table in Appendix B also provides a descriptive summary of these findings. All reported coefficients were generic (i.e., the same for all alternatives) except the coefficient of the fuel availability attribute, which was only specified for the biofuel and electric-car alternatives.

Overall, we identified significant variations in respondents' car-purchase intentions countries. These variations reflected significant (random) taste heterogeneity in respondents' choices, which – unlike a mixed multinomial logit (MXL) in which the estimated parameters follow a continuous distribution, was captured by a number of latent classes (i.e., two classes in this study). Each class was associated with a set of parameter estimates corresponding to the utility function of each car alternative (i.e., petrol, biofuel, electric and hybrid). Most importantly, LCMs can link taste heterogeneity with the socio-economic characteristics of respondents and socio-psychological scales mentioned in Section 2.2. This is a useful element in the analysis of taste heterogeneity when compared with MXL in which we simply know that sensitivity in choices follows an assumed random distribution (Beck et al., 2013). We discuss the details of these findings in the following subsections.

*Germany*

For Germany, the analysis identified two classes of respondents with contrasting choices in terms for autonomous driving levels and car technology/fuel. Respondents in Class 1 were less likely to choose a car with Driver Assistance (Level 1), High Automation (Level 4) and Full Automation (Level 5). Class 1 included individuals who were less likely to self-report a green identity, were more conservative about new technologies and drove in rural areas. As with all other countries, Class 2 was the reference class against which all respondent profiles are compared with. As shown from the values of the alternative specific constants in Tables 5 and 6, the profile of German respondents in Class 1 aligned with their intention – all else being equal, to purchase petrol and a hybrid (significant at 90%) cars instead of biofuel or electric cars. On the other hand, Class 2 respondents were in favour of cars with Partial Assistance (Level 2), High Automation (Level 4) and Full Automation (Level 5). All else being equal, Respondents in Class 2 were not in favour of Petrol cars and were more likely to choose Electric cars, relative to Biofuel, the reference level.

[5] Number of observations = Number of cases / 4 alternatives

In terms of other vehicle characteristics, German respondents in Class 1 were more likely to choose large and medium sized cars and less likely to opt-in for cars made of climate-neutral conventional materials. Class 2 respondents were more likely to choose medium sized cars (vs. small). They were less sensitive to price and fuel availability but more sensitive to running costs when compared with Class 1 respondents. Finally, Class 2 respondents were more likely to choose cars made of climate-neutral and ethically sourced organic materials.

*India*

Respondents in Class 1 of the Indian sample were in favour of Conditional Automation (Level 3) and Full Automation (Level 5), the latter was significant at the 90% confidence level. They were also more likely to choose Electric and Hybrid cars. In terms of their socio-economic and attitude profile, respondents in Class 1 (and relative to Class 2) self-identified as environmental-friendly individuals who had a University degree and followed technological development (high innovativeness). Respondents in Class 2, on the other hand, were in favour of Petrol cars and were indifferent to any level of automation relative to No Driving Automation (Level 0), the reference level.

Respondents in Class 1 were more likely to choose medium sized and large cars with unique design whereas Class 2 respondents placed higher value on medium sized cars to small or large cars and placed no value on the design of the car. Overall, Respondent in Class 2 were more sensitive to the purchase price of the car (relative to Class 1) whereas Respondents in Class 1 were also sensitive to fuel availability given their (on average) higher preferences for Electric cars relative to respondents in Class 2. Interestingly, both Classes of respondents were not sensitive to running costs. Finally, respondents in Class 1 were more likely to choose cars made of any type of material other than conventional materials and climate-neutral conventional materials. On the other hand, Class 2 respondents were less likely to choose cars made of organic materials.

*Japan*

Japanese respondents also formed two classes. Class 1 respondents were older than those in Class 2 as age was the only statistically significant variable among the socio-economic and attitudinal variables that differentiated the two classes (see, Table 6). Respondents in Class 1 were in favour of Electric and Hybrid cars equipped with Partial Assistance (Level 2), Conditional Automation (Level 3), and High Automation (Level 4). On the other hand, those in Class 2 were also likely to choose Petrol, Electric and Hybrid cars relative to Biofuel, the reference level. These younger respondents in Class 2, relative to Class 1, were in favour of Driver Assistance (Level 1; significant at 90% confidence level), Conditional Automation (Level 3), High Automation (Level 4; significant at 90% confidence level) and Full Automation (Level 5; significant at 95% confidence level).

Respondents in Class 1 were less sensitive to price but overall, they were more sensitive to running costs, fuel availability and acceleration of the car relative to respondents in Class 2. Finally, Japanese respondents in Class 1were indifferent to any type of materials when compared to conventional materials and respondents in Class 2 were less likely to choose ethically sourced conventional materials.

## Table 5. Estimated coefficients of discrete choice latent class models across six countries

| | Germany | | India | | Japan | | Sweden | | UK | | US | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Class 1* | *Class 2* | *Class 1* | *Class 2* | *Class 1* | *Class 2* | *Class 1* | *Class 2* | *Class 1* | *Class 2* | *Class 1* | *Class 2* |
| Probability of membership | 0.561 | 0.439 | 0.481 | 0.519 | 0.528 | 0.472 | 0.504 | 0.496 | 0.593 | 0.407 | 0.663 | 0.337 |
| Running Cost | -1.546*** | -1.923*** | -0.126* | -0.177* | -1.117*** | 0.199 | -0.084*** | -0.084*** | -1.691*** | -2.278*** | -1.150*** | -3.028*** |
| Price>> | -1.657*** | -0.587*** | -0.919*** | -1.177*** | -0.205* | -0.873*** | -0.495*** | -1.135*** | -1.949*** | -0.366** | -1.057*** | -0.788*** |
| Autonomous Driving: | | | | | | | | | | | | |
| Level 0 – No automation | Reference level | | | | | | | | | | | |
| Level 1 - Driver assistance | -0.290** | 0.168 | 0.062 | 0.076 | 0.084 | 0.332* | -0.111 | -0.119 | -0.366*** | -0.093 | -0.133 | -0.219 |
| Level 2 - Partial assistance | -0.274 | 0.316* | 0.030 | -0.083 | 0.362** | 0.214 | -0.204 | -0.115 | -0.452*** | -0.017 | -0.204 | 0.060 |
| Level 3 - Conditional automation | -0.205 | 0.451*** | 0.217* | 0.036 | 0.407*** | 0.487*** | -0.078 | -0.160 | -0.412*** | -0.143 | -0.126 | 0.258 |
| Level 4 - High automation | -0.406*** | 0.197 | 0.205 | -0.115 | 0.455*** | 0.302* | -0.279* | -0.124 | -0.595*** | -0.088 | -0.367*** | -0.056 |
| Level 5 - Full automation | -0.533*** | 0.299* | 0.266* | 0.121 | 0.118 | 0.510** | -0.378*** | -0.357** | -0.322** | -0.225 | -0.630*** | 0.078 |
| Conventional Materials^ (CMs) | Reference level | | | | | | | | | | | |
| Ethically sourced CMs | 0.142 | 0.248 | 0.200 | 0.179 | 0.110 | -0.469** | 0.024 | -0.138 | 0.411*** | 0.175 | 0.036 | -0.015 |
| Climate-neutral CMs | -0.362*** | -0.004 | 0.271* | -0.234 | 0.197 | -0.281 | 0.096 | 0.0113 | 0.278** | 0.227 | 0.037 | 0.228 |
| Organic materials (OMs) | -0.053 | 0.181 | 0.503*** | -0.285* | -0.053 | -0.078 | 0.156 | 0.0876 | 0.469*** | -0.217 | -0.020 | -0.094 |
| Climate-neutral OMs | -0.032 | 0.303* | 0.412*** | -0.105 | -0.133 | -0.105 | 0.196 | -0.118 | 0.309** | 0.171 | 0.096 | -0.054 |
| Ethically sourced OMs | 0.011 | 0.378*** | 0.321** | -0.077 | 0.106 | -0.291 | 0.347*** | -0.091 | 0.459*** | 0.483*** | 0.010 | 0.071 |
| Fuel Availability | 0.014*** | 0.009** | 0.015*** | -0.001 | 0.009** | 0.006 | 0.003 | 0.006 | 0.011*** | 0.013*** | 0.016*** | 0.009** |
| Acceleration | 0.011 | 0.018 | 0.057*** | 0.007 | -0.050** | -0.041* | -0.007 | -0.062*** | -0.005 | -0.009 | -0.007 | -0.087*** |
| Vehicle Size: Small | Reference levels | | | | | | | | | | | |
| Medium | 0.430*** | 0.380*** | 0.408*** | 0.235* | 0.089 | 0.109 | -0.038 | 0.482*** | 0.005 | 0.297** | 0.525*** | -0.024 |
| Large | 0.203** | 0.143 | 0.520*** | 0.062 | -0.619*** | -0.247* | 0.086 | 0.309*** | 0.071 | -0.034 | 0.406*** | -0.062 |
| Design: Unique (vs. Conventional) | -0.099 | 0.027 | 0.198** | 0.103 | -0.165* | -0.248** | -0.012 | 0.105 | 0.100 | -0.087 | 0.065 | 0.010 |
| Alternative Specific Constants | | | | | | | | | | | | |
| Petrol | 1.243*** | -0.611** | -0.583 | 0.962*** | -0.362 | 2.101*** | -1.270*** | 0.935*** | 1.264*** | -1.419*** | 0.509** | -0.448 |
| Electric | 0.118 | 0.512*** | 0.318** | -0.015 | 0.405*** | 1.303*** | 0.438*** | 0.090 | 0.517*** | 0.124 | -0.387*** | 0.602*** |
| Hybrid | 0.425* | 0.257 | 0.474** | -0.439 | 0.440** | 1.948*** | 0.448*** | 0.465** | 0.470*** | 0.123 | 0.201 | 0.363* |
| Nr. of cases | 9240 | | 10620 | | 7820 | | 9880 | | 10180 | | 10840 | |
| Nr. of observations | 2310 | | 2655 | | 1955 | | 2470 | | 2545 | | 2710 | |
| Nr. of individuals | 462 | | 531 | | 391 | | 494 | | 509 | | 542 | |
| Number of parameters | 49 | | 48 | | 49 | | 49 | | 49 | | 49 | |
| Log-likelihood at convergence | -2831 | | -3468 | | -2372 | | -3170 | | -3144 | | -3283 | |
| $Rho^2$ | 0.12 | | 0.06 | | 0.12 | | 0.07 | | 0.11 | | 0.13 | |
| Adjusted-$Rho^2$ | 0.10 | | 0.05 | | 0.11 | | 0.06 | | 0.09 | | 0.11 | |

*** significant at 99% confidence level; ** significant at 95% confidence level; * significant at 90% confidence level

>> Price and running cost are scaled as follows: Germany, UK, US: price/10,000; running cost/1000 - Sweden: price / 100000; running cost/1000 – India: price / 1000000; running cost/10000; Japan price / 1000000; running cost/10000; ^ Conventional = steel, aluminium and plastic. Organic = wood fibre, soybeans and flax.

**Table 6. Class membership model estimates**

| | **Germany** | **India** | **Japan** | **Sweden** | **UK** | **US** |
|---|---|---|---|---|---|---|
| Classes± | *Class 1* | *Class 1* | *Class 1* | *Class 1* | *Class 1* | *Class 1* |
| Self-reported green identity (environmental-friendly stance) | -0.548*** | 0.560** | 0.254 | 0.591*** | -0.298 | -0.685*** |
| Age | 0.003 | -0.017 | 0.029* | 0.011 | 0.020** | 0.011 |
| University degree | -0.427 | 0.936*** | 0.010 | 0.470* | 0.122 | -0.225 |
| Self-reported high knowledge of sustainability of materials used in car manufacture | -0.061 | 0.065 | 0.016 | -0.003 | -0.074 | 0.081 |
| Self-reported low innovativeness (conservative to use new technologies) | 0.468*** | -0.531*** | 0.213 | -0.554*** | 0.650*** | 0.195* |
| Female | -0.321 | 0.043 | -0.193 | 0.479* | 0.338 | -0.299 |
| Children | 0.361 | 0.093 | -0.256 | -0.259 | 0.232 | 0.086 |
| Mostly drive in urban areas | -0.454* | 0.435 | -- | -0.432 | -0.585** | -0.224 |
| Constant | 1.412 | -2.330*** | 0.254 | -0.953 | -0.973 | 1.784** |

± Class 3 is the reference class
-- Data missing

*Sweden*

Swedish respondents in Class 1 – when compared with those in Class 2, were more likely to be females with a university degree who followed technological development (high innovativeness). These respondents were in favour of Hybrid and Electric cars and were against Petrol cars equipped with High Automation (Level 4) and Full Automation (Level 5); they were also indifferent to the other autonomous driving levels when compared to No Automation (Level 0), the reference level. Swedish respondents in Class 2 were more likely to choose Petrol and Hybrid cars but were not in favour of cars equipped with Full Automation (Level 5).

Respondents in Class 1 were indifferent to car size and design but would prefer cars made of ethically sourced organic materials. By contrast, Respondents in Class 2 were more likely to opt-in for a medium sized or large car and were more price sensitive relative to those in Class 1. Finally, respondents in Class 2 were indifferent to the type of materials used to make cars relative to Conventional Materials, the reference level.

*UK*

UK respondents in Class 1 were older individuals, conservative about new technologies (low innovativeness) who mostly drove in rural areas. Class 1 respondents were against any level of autonomous driving as shown from the negative coefficients of the corresponding attributes in Table 5. This Class was in favour of Petrol, Electric and Hybrid cars relative to Biofuel cars. Member of Class 2 were less likely to choose Petrol cars and were indifferent to any autonomous-driving levels.

The members of Class 1 were sensitive to price, running cost and fuel available, but their choices were less influenced by variations in the size, design and acceleration of the car options. It is reasonable to assume that this Class of respondents see the car as a practical way to keep them mobile. The members of Class 2 in the UK sample were more likely to choose medium sized cars, were less sensitive to purchase price but more sensitive to running cost, relative to respondents in Class 1. Both groups of respondents placed almost equal importance on fuel availably. Finally, members of Class 1 were more likely to choose a car made of any type of material other than conventional materials whereas those in Class 2 were in favour of ethically sourced organic materials.

*US*

Lastly, US respondents also formed two classes. Relative to Class 2, respondents in Class 1 were individuals who were less likely to self-identify as green and were conservative about new technologies (low innovativeness). They more likely to choose Petrol and less likely to opt-in for an Electric car. They were also not in favour of car options with High Automation (Level 4) and Full Automation (Level 5). On the other hand, Respondents in Class 2 would prefer an Electric and to a lesser extent a Hybrid car relative to Biofuel or Petrol car. Members of Class 2 were indifferent to any level of automation, size, design of the car. Class 2 member expressed higher sensitivity against the running cost of the car and fuel availability and lower sensitivity for purchase price relative to members of Class 1. Both classes placed no value on the type of materials used to make the car.

## 5. Willingness to pay and accept autonomous driving

Table 7 presents a summary of marginal WTP and willingness to accept (WTA) estimates for autonomous-driving levels across market segments (classes) and countries, which were statistically significant at the 95% confidence level. Conditional Automation (Level 3) appears as a natural break across automation levels for Japan and Germany. Japanese buyers (Class 1) were willing to pay an average of €4686 and German (Class 2) consumers an average of €7682, which was the overall maximum WTP across autonomous driving levels and countries. Broadly speaking, the values are within the range of values reported in previous studies (Bansal et al., 2016; Daziano et al., 2017; Jiang et al., 2018). This study also revealed population segments, which were against autonomous driving levels. We estimated marginal WTA values, especially for cars with Full Automation (Level 5), ranging from €1853 in the UK to €7180 in the Sweden.

Respondents across all countries, except the UK, were indifferent across Zero Automation (Level 0), Driver Assistance (Level 1) and Partial Assistance (Level 2). UK respondents in Class 1 would accept Driver Assistance (Level 1) should they have received a discount of €2105 and Partial Assistance (Level 2) should the compensation been €2597, respectively. This finding may not necessarily reflect respondents' deterrence for such technologies, but they might have expected these features to be standard and hence, they would not be willing to pay extra. Differentiated views may also be explained by the profiles of UK respondents in that class. As shown in Table 6, UK respondents in Class 1 were more likely to be older, conservative about new technologies and who drove in rural areas. Overall, UK participants in Class 1 were the only group against any level of autonomous driving.

The majority of consumer segments placed no value on High Automation, whereas some German (Class 1), UK (Class 1) and US (Class 1) respondents would expect an average price reduction equal to €2450, €3421 and €3158 to purchase a car with this autonomous driving feature, respectively.

**Table 7. Marginal WTP/WTA values for autonomous driving levels (in** €)

| | | Autonomous Driving Level | | | | |
|---|---|---|---|---|---|---|
| Country | Class | Level 1 Driver assistance | Level 2 Partial assistance | Level 3 Conditional automation | Level 4 High automation | Level 5 Full automation |
| Germany | Class 1 | | | | -2450 (-4416:-483) | -3215 (-5305:-1128) |
| | Class 2 | | | 7682 (1799:13565) | | |
| Japan | Class 1 | | | 4686 (727:8645) | | 4901 (642:9160) |
| Sweden | Class 1 | | | | | -7180 (-13397:-964) |
| | Class 2 | | | | | -2958 (-5893:-25) |
| UK | Class 1 | -2105 (-3654:-565) | -2597 (-4318:-877) | -2369 (-2853:-886) | -3421 (-5156:-1687) | -1853 (-3431:-275) |
| US | Class 1 | | | | -3158 (-5495:-822) | -5421 (-7968:-2875) |

*All values are in Euros (exchange rate as of 14/09/2019)*
*Marginal WTP/WTA [lower and upper quartiles in brackets using the Delta method (Hole, 2007)]*
*India, Japan (Class 2), UK (Class 2) and US (Class 2) are not listed as none of the marginal WTP/WTA estimates were statistically significant at 95% or higher*

Finally, only respondents in Japan were willing to pay extra (€4901) to purchase a car with full automation (Level 5). Respondents in other countries presented a wide range of WTA values including €3215 in Germany (Class 1), €7180 (Class 1) and €2958 (Class 2) in Sweden, €1853 in the UK (Class 2) and €5421 in the US (Class 1). Overall, an identified group of German and US consumers (Class 1) exhibit similar, WTA reactions to different autonomous driving levels 4 and 5. As shown in Table 6, it is noteworthy that these German and US consumers share similar characteristics as both classes were negatively associated with self-identifying as green and positively associated with self-reported low innovativeness. There was also a tendency (although not significant in Germany) to drive less in urban areas. The negative self-reported, low innovativeness association and low tendency to drive in urban areas was also seen in the UK Class 1 and in Class 1 of the Swedish respondents (although driving less in urban areas was not statistically significant). However, in contrast to Germany and the US, membership of Class 1 in the Swedish participants was *positively* associated with self-identifying as green.

## 6. Discussion and Conclusion

This paper explored consumers' stated intentions to purchase a self-driving car among Petrol, Electric, Hybrid and Biofuel powered options using a stated choice discrete choice experiment. Respondents' intentions to purchase such cars were examined across Germany, India, Japan, Sweden, UK and US. The analysis employed Latent Class Discrete Choice Models as the focus of the study was to identify and explore differences across segments in the country samples when respondents considered purchasing a car. This is one of the first studies to explore the unobserved heterogeneity of consumer preferences regarding autonomous vehicles when considering alternative fuelled vehicle options across different country settings.

A key finding of the LCM analysis and the WTP/WTA values is the significant heterogeneity in preferences for autonomous-driving levels both within and across countries. The between country differences support the cross-country surveys of public acceptance of autonomous vehicles. Indeed, the WTP values found in this study being highest in Japan and only for Conditional Automation for one class in Germany, were in line with survey findings by Continental (2018) which found that a higher percentage of Japanese participants saw AVs as a sensible advancement and that a higher percentage of German participants intended to use assisted driving technologies compared to participants in the US, China, and respectively, Germany and Japan. Reasons for this greater preference for high and full automation in Japan could relate to the country being increasingly characterised as having a high technology based economy (Breheny and McQuaid, 2018) or to the anticipation of challenges related to an ageing population, a segment for whom AVs are argued to offer the most benefits (Fagnant and Kockelman, 2015). At the same time, the WTA values found for the German (Class 1), Swedish, UK and UK samples, support the discomfort with AVs observed by Hudson et al. (2019) in multiple European countries. On the other hand, the WTA values estimated for a segment of the US sample was contrary to previous studies, which reported that US consumers would prefer cars with autonomous-driving features (Schoettle and Sivak, 2014). A possible explanation for these contrasting findings may relate to the recent accidents involving autonomous vehicles in the US (Continental, 2018; The Guardian, 2018). However, further research to explore values and further cultural aspects that could underpin AV acceptance will be needed to explain the differences identified here. Further research should also focus on whether and why consumer purchase intentions for cars with autonomous-driving features – especially those with high or full automation, may change.

Regarding autonomous driving features, the within country (class) differences support previous findings suggesting that the WTP amounts can vary greatly across individuals, despite a positive average (Daziano et al., 2017; Kyriakidis et al., 2015). For example, a contrasting pattern in preferences was observed in Germany where respondents allocated in Class 2 (the reference class) were willing to pay for Conditional Automation (Level 3) whereas those in Class 1 were less likely to choose cars with High Automation (Level 4) and Full Automation (Level 5). The latter class included individuals who self-reported low innovativeness, had low environmental-friendly stance and drove in rural areas. Also, in Japan, although there was a group of respondents who were indifferent to the different levels of automation (Class 2), respondents in Class 1 were in favour of Conditional Automation (Level 3) and Full Automation (Level 5). The latter class comprised younger respondents relative to Class 2, which was the reference class. This finding for Japanese respondents is in line with previous work reporting that younger individuals were more likely to belong to the 'driverless class' (Bansal et al., 2016; Hudson et al., 2019; Hulse et al., 2018), but not in the case of the UK respondents.

These insights into the heterogeneity of preferences across the different countries and within each country is valuable for policymakers, the automotive industry and technology innovators who focus on autonomous driving. Identifying potential early adopters or certain user groups willing to pay for autonomous cars is useful to be able to estimate future market shares and willingness-to-adopt these cars.

Our findings also extend and support the adopter segments from electric vehicles (Noppers et al., 2015) to autonomous vehicles. We observed that individuals who identified themselves as being ‘innovative’ (e.g. ‘tech-friendly’/innovation adopters) were more likely to choose cars with increased levels of autonomous driving. For example, Indian respondents who self-identified as being innovative were more likely to choose cars with increased levels of autonomous driving. Also, respondents in Germany, UK and the US who were less likely to self-report as being innovative were more likely to opt-in for lower levels of automation.

Contrary to previous findings on AV ownership (Haboucha et al., 2017; Lavieri et al., 2017) self-reporting green identity was associated with those classes of respondents that valued higher levels of autonomous driving. This exception to this trend was Sweden where respondents who self-identified as ‘green’ belonged to the class which valued higher levels of automation. This positive association in Sweden might be due to participants perceiving AVs as having potential environmental benefits, however, as the potential impacts of AVs are largely speculative and contested at this time (Whittle et al., 2019), further research will be needed to better understand this association. These classes also included positive effects for cleaner (Hybrid, Electric) vehicles rather than Petrol cars (e.g. Germany, India, Japan, but not in the UK and Sweden), which is in line with previous literature on preferences for alternative fuels and green identity (Barbarossa et al., 2015), however, the lack of significant associations (UK and Sweden) may stem from scepticism over the environmental benefits of alternative fuels, such as electricity (Degirmenci and Breitner, 2017).

Additional socio-demographic variables that had an effect on class membership included the negative correlation of respondents who mostly drove in urban areas with higher levels of autonomy (Germany, UK). Respondents who mostly drove in rural areas were less likely to choose higher (or any) levels of autonomous driving, which perhaps relates to differences in perceived transport needs and preferences between rural and urban road users, that could be explored further. Also, higher education qualification (i.e., university degree or higher) of respondents was positively associated with higher levels of autonomous driving in India, but (marginally) negatively correlated in Sweden. Older respondents were less likely to choose higher autonomous driving levels in the UK. Finally, gender or having children was not a statistically significant predictor of any class membership across all countries.

A significant contribution of this study is that it considers the choice of autonomous driving levels in the context of choosing among different car technologies and fuels including Petrol, Hybrid, Electric and Biofuel. LCM estimations revealed a pattern of joined preferences for electric cars and fully automated cars (Level 5) in Japan. Both classes in the Japanese sample were more in favour of electric and hybrid cars and varying levels of autonomy. On the other hand, US respondents allocated in Class 2 were not in favour of electric or fully autonomous driven cars. There were also classes in which respondents were more likely to choose electric vehicles, but were against higher levels of automation (Sweden, UK) and others that respondents were more likely to choose electric cars and were positive to higher levels of automation (Germany, India, Japan). These within class and cross-national differences suggest that a preference for innovation in one aspect of a vehicle (e.g. fuel) may not always translate into preferences for innovation in other aspects of the vehicle (e.g. automation), contrary to what might be predicted from technological diffusion literature, for instance (Rogers, 2010).

Regarding petrol vehicles, half of the latent classes revealed a contrasting pattern between increased levels of autonomous driving and the purchase of a petrol cars

(Germany, UK, US), with a preference for petrol pairing with an avoidance of automation in one class and vice versa in the other class. Sweden and Japan were the exceptions, with both classes showing a preference for automation in Japan and both classes showing an avoidance of automation in Sweden, despite showing different class preferences for petrol. In India, Class 2 revealed strong preference towards Petrol vehicles, while not exhibiting significant effects for any level of autonomous driving. As AFV and AV technologies advance and are implemented, understanding how the acceptance of the two technologies interrelate and are perceived across countries and consumer groups will be important for their promoting and future adoption.

Another significant contribution of this study was the evidence that in some cases we estimated significant levels of WTA values, which implied that respondents would like to receive a discount to purchase a car with increased levels of autonomous driving (i.e., UK, US, Sweden and some cases in Germany). We can only make an attempt to interpret as to why there was this aversion to autonomous driving. As noted, we stated in the choice experiment that the autonomous driving capabilities could be turned off and the car driven "as normal" for levels 1 to 4. As such, the observed aversion to these levels may be more related to concerns for safety, technical failures and privacy threats (Bansal et al., 2016; Kyriakidis et al., 2015; Schoettle and Sivak, 2014) than to a feared loss of driving pleasure or an unwillingness to relinquish control (Howard and Dai, 2014). However, the relatively high WTA for level 5 (in which the vehicle could not be manually driven) seen in Sweden, Germany and the US may have resulted from a combination of these concerns. The need to offer discounts for vehicles with autonomous driving capabilities is important for policymaking and market research as it shows that there are respondents who perceived autonomous driving negatively. This may be a barrier as future planning of transport systems envisages the presence of autonomous cars. Better identification and exploration of the population segments that are against ownership of autonomous vehicles and the reasons for these perceptions would provide valuable input for future strategy and policymaking relating to vehicles with autonomous capabilities.

Finally, there are two points worth of future investigation and consideration to improve policy recommendations. Firstly, the stated choice experiment primarily examines *purchase intentions* of consumers rather than actual purchases. The latter has been a long-standing critique of this approach. For example, under a hypothetical choice situation WTP (or WTA) may be under-estimated (or over-estimated) either because participants may be expressing high levels of environmental concern, exhibiting high innovativeness or exhibiting a 'protest' behaviour against autonomous driving. Having said that, a carefully designed choice experiment allows to assess and quantify trade-offs within a realistic setting. Most importantly, the application of a carefully designed stated choice experiment conducted across a number of countries allowed for our study to minimise the risk of biased estimates and derive internally valid consumer purchase intentions and valuations of different autonomous-driving levels. An improved (ideal) approach would be to study car choices before and after trials with consumers using different levels of autonomous driving and car technologies.

Secondly, the LCM approach employed in this study has pointed to a number of classes with a discrete set (one per class) of coefficients being estimated. The profile of respondents who are likely to be members of that class has been described by socio-economic and attitudinal scales. Attitudinal scales are directly specified in the membership model as if they represent latent (unobserved) variables and thus entail a risk of inducing endogeneity (i.e., the systematic part of the utility being correlated with the error term) in the class membership model. One computationally intensive way to correct for this endogeneity would be the class membership model to be an Integrated Latent Variable and Choice (ICLV) model instead of an MNL but software to accommodate this model estimation is not widely available yet (see, Daly et al., 2012; Guevara and Ben-Akiva, 2010; Hess et al., 2013).


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## Appendix A. Descriptive Statistics of innovativeness, knowledge materials and green identity

| ***Innovativeness***<br>I am the type of person who… | **GER** | **IND** | **JAP** | **SWE** | **UK** | **US** |
|---|---|---|---|---|---|---|
| [1] Closely follow new technological developments and who dares taking risks by being the first to purchase an innovative car. (high innovativeness) | 104 (10.3) | 483 (44.8) | 37 (3.6) | 125 (12.6) | 118 (12.9) | 71 (7.1) |
| [2] Envisions potential advantages in innovative cars and who is one of the first to make use of these advantages and to profit from those. | 169 (16.7) | 192 (17.8) | 76 (7.5) | 120 (12.1) | 115 (12.5) | 82 (8.2) |
| [3] Is interested in innovative cars, but at the same time is pragmatic. First, I would like to take time and be persuaded by the advantages that an innovative car possesses. My decisions are (mainly) based on the recommendations of existing users. | 399 (39.4) | 275 (25.5) | 268 (26.4) | 324 (32.7) | 290 (31.6) | 332 (33.4) |
| [4] Is not thrilled by innovative cars, but who rather appreciates security. It is safe to purchase an innovative car when it has been on the market for some while and offers obvious advantages. | 191 (18.9) | 87 (8.1) | 393 (38.6) | 268 (27.1) | 223 (24.3) | 334 (33.6) |
| [5] Is traditional and has little affinity with innovative car. I do not like changes in life and I purchase an innovative car only when the existing model I use is not produced anymore. (low innovativeness) | 135 (13.3) | 42 (3.9) | 231 (22.7) | 151 (15.3) | 166 (18.1) | 176 (17.7) |
| Prefer not to say | 14 (1.4) | 118 (10.9) | 12 (1.2) | 2 (0.2) | 5 (0.6) | 4 (0.4) |
| | **Number of individuals with score > 6 (%)**<br>*(1: Nothing at all – 10: A great deal)* | | | | | |
| ***Knowledge about materials*** | | | | | | |
| *How much do you know about the sustainability of the materials that cars are made from?* | 219 (21.6) | 670 (60.6) | 146 (14.5) | 253 (25.6) | 190 (20.7) | 201 (20.1) |
| ***Green Identity*** | **Number of individuals who agreed or strongly agreed (%)** | | | | | |
| [1] I think of myself as an environmentally friendly person | 541 (53.5) | 948 (86.3) | 348 (34.5) | 524 (53.1) | 528 (57.6) | 614 (61.5) |
| [2] I think of myself as someone who is very concerned with environmental issues | 471 (46.5) | 898 (81.7) | 328 (32.7) | 425 (43.0) | 482 (52.6) | 532 (53.3) |
| [3] I would be embarrassed to be seen as having an environmentally friendly lifestyle | 104 (10.3) | 448 (40.8) | 108 (10.7) | 149 (15.1) | 129 (14.1) | 91 (9.1) |
| [4] I would not want my family or friends to think of me as someone who is concerned about environmental issues. | 135 (13.3) | 448 (40.7) | 108 (10.7) | 244 (24.8) | 145 (15.7) | 132 (13.2) |
| **Total** | **1,012** | **1,106** | **1,009** | **990** | **917** | **999** |

## Appendix B. Summary of findings from the LCM

| Country | | Class 1 | Class 2 |
|---|---|---|---|
| **Germany** | *Class members* | • Less likely to self-report green identity<br>• Conservative about technologies (low innovativeness)<br>• Mostly drive in rural areas | Reference class |
| | *Class preferences* | • More likely to choose Petrol and Hybrid<br>• Less likely to choose autonomous-driving levels 1, 4 and 5; indifferent to Levels 2 and 3 vs. Level 0<br>• More likely to opt in for large and medium sized cars than small cars<br>• Sensitive to price, running costs, fuel availability<br>• Less likely to choose cars made of climate-neutral conventional materials | • In favour of Electric and less likely to choose Petrol<br>• In favour of cars with autonomous driving levels 2, 4 and 5 (marginally significant)<br>• More likely to choose medium sized cars (vs. small or large)<br>• Less sensitive to price and fuel availability but more sensitive to running costs compared with Class 1<br>• More likely to choose cars made of climate-neutral and ethically sourced organic materials |
| **India** | *Class members* | • Self-identify as green<br>• Have university degree<br>• Follow technological development (high innovativeness) | Reference class |
| | *Class preferences* | • More likely to choose Electric and Hybrid cars (vs. Petrol and Biofuel)<br>• More likely to choose autonomous driving levels 3 and 5 (significantly at 90%)<br>• Would prefer medium and large cars with unique design<br>• Sensitive to price and fuel availability but not running costs<br>• Would prefer any type of material other than conventional materials and climate-neutral conventional materials | • More likely to choose Petrol cars<br>• Indifferent to any level of automation relative to Level 0<br>• Would prefer medium cars<br>• More sensitive to price relative to Class 1<br>• Less likely to choose cars made of organic materials |
| **Japan** | *Class members* | • Older | Reference class |
| | *Class preferences* | • More likely to choose Electric and Hybrid<br>• In favour of autonomous driving levels 2, 3, and 4<br>• Less likely to opt-in for large cars with conventional design<br>• Sensitive to price, running costs, fuel availability and acceleration<br>• Indifferent to any type of materials against conventional materials | • More likely to choose Petrol, Hybrid and Electric<br>• In favour of autonomous driving levels 1, 3, 4 and 5<br>• Less likely to opt-in for large cars with unique design<br>• Sensitive to price, acceleration, but not running costs<br>• Less likely to choose ethically sourced conventional materials |
| **Sweden** | *Class members* | • Self-identify as green<br>• Have university degree<br>• Follow technological development (high innovativeness)<br>• More likely to be female than male | Reference class |
| | *Class preferences* | • More likely to choose Hybrid and Electric and less likely to choose Petrol relative to Biofuel<br>• Not in favour of autonomous driving levels 4 and 5<br>• Indifferent to car size and design<br>• Sensitive to price and running costs<br>• Would prefer cars made of ethically sourced organic materials | • More likely to choose Petrol and Hybrid<br>• Not in favour of autonomous driving level 5<br>• More likely to opt-in for a medium sized or large car<br>• Sensitive to price (higher than Class 1), running cost and acceleration<br>• Indifferent to any type of materials |

| | | | |
|---|---|---|---|
| **UK** | *Class members* | • Older<br>• Conservative about technologies (low innovativeness)<br>• Mostly drive in rural areas | Reference class |
| | *Class preferences* | • More likely to choose Petrol, Electric and Hybrid relative to Biofuel<br>• Against any level of autonomous driving<br>• Indifferent to size, design and acceleration<br>• Sensitive to price, running cost and fuel availability<br>• More likely to choose a car made of any type of material other than conventional materials | • Less likely to choose Petrol<br>• Indifferent to any autonomous driving levels<br>• Would opt-in for a medium sized car<br>• Less sensitive to price but more sensitive to running cost relative to Class 1; equal importance to fuel availability as in Class 1<br>• More likely to choose ethically sourced organic materials |
| **US** | *Class members* | • Less likely to self-report green identity<br>• Conservative about technologies (low innovativeness) | Reference class |
| | *Class preferences* | • More likely to choose Petrol and less likely to opt-in for an Electric car<br>• Less likely to choose cars with autonomous driving levels 4 and 5<br>• In favour of medium sized and large cars<br>• Sensitive to price, running cost and fuel availability<br>• Indifferent to any type of materials | • More likely to choose Electric and Hybrid<br>• Indifferent any level of autonomous driving<br>• Indifferent to car size and design<br>• Sensitive to price (higher than Class 1), running cost (lower than Class 1), fuel availability and acceleration<br>• Indifferent to any type of materials |