ETH zürich

ETH Library

Comfort with varying levels of human supervision in self-driving cars: Determining factors in Europe

Journal Article

Author(s):
Kaszas, Daniel; Roberts, Adam Charles

Publication date:
2023-09

Permanent link:
https://doi.org/10.3929/ethz-b-000570329

Rights / license:
Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International

Originally published in:
International Journal of Transportation Science and Technology 12(3), https://doi.org/10.1016/j.ijtst.2022.08.001

This page was generated automatically upon download from the ETH Zurich Research Collection.
For more information, please consult the Terms of use.

International Journal of Transportation Science and Technology 12 (2023) 809–821

Contents lists available at ScienceDirect

International Journal of Transportation Science and Technology

journal homepage: www.elsevier.com/locate/ijtst

Comfort with varying levels of human supervision in self-driving cars: Determining factors in Europe

Daniel Kaszas [a], Adam Charles Roberts [a,b,*]

[a] ETH Zürich, Zürich, Switzerland
[b] Singapore-ETH Centre, Future Resilient Systems Programme, CREATE campus, Singapore

ARTICLE INFO

Article history:
Received 25 August 2021
Received in revised form 7 July 2022
Accepted 6 August 2022
Available online 11 August 2022

Keywords:
Human supervision
Third-party supervision
Technology acceptance
Autonomous vehicles

ABSTRACT

While numerous studies have investigated attitudes towards self-driving cars in general, less research attention has been focused on individuals' comfort with the presence (or absence) of third-party human supervision of this automation, and its potential correlates. In the present study we perform a secondary analysis of pre-existing data from The European Commission's Eurobarometer 92.1, a large-scale European survey ($n = 27565$) of expectations and concerns of connected and automated driving. By comparing responses to three levels of human supervision in self-driving cars, we aim to identify changes in the importance of predictors of comfort with automation. We find considerable heterogeneity in both individual attitudes, as well as in country-level attitudes in our descriptive analysis. We find a trend of decreasing comfort as external human supervision is reduced, although this effect differs between countries. We then investigate potential drivers of self-reported comfort with varying levels of external human supervision in a regression framework. Gender differences get stronger with decreasing supervision, suggesting a possible resolution to conflicting evidence in previous studies. Following this, we fit an ordinal random forest model to derive variable importance metrics, which enable us to compare the changing role predictor variables might play in shaping self-reported comfort, depending on varying levels of third-party supervision. Data privacy is highlighted as an important variable, regardless of level of supervision. Our findings provide confirmation for previous literature in a large sample, while also uncovering a number of novel associations, providing guidance for future policy-making and research efforts.
© 2022 Tongji University and Tongji University Press. Publishing Services by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Recent advances in the field of machine learning and computer vision have rapidly accelerated the development of autonomous vehicles (AVs). While some level of automation has been present in commercially available vehicles since the introduction of cruise control (Teetor, 1950), the component parts of a car capable of fully autonomous driving in urban environments are only now all coming into place (Badue et al., 2020). Consequently, any successes or obstacles experienced by AV industry-leaders (such as Alphabet subsidiary Waymo or GM subsidiary Cruise) are followed by considerable public interest (Chan, 2017; Awad et al., 2020b). There are a number of different classification systems to characterize autonomous vehicles (SAE, 2014; NHTSA, 2013; Sousa et al., 2018). For example, the UNECE (United Nations Economic Commission for

Peer review under responsibility of Tongji University and Tongji University Press.
* Corresponding author.
E-mail address: adamcharles.roberts@sec.ethz.ch (A.C. Roberts).

https://doi.org/10.1016/j.ijtst.2022.08.001
2046-0430/© 2022 Tongji University and Tongji University Press. Publishing Services by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Europe) defines six Functional Categories of Automated Function, which emphasise generic functional requirements for policymaking and safety. In contrast, the most commonly used Level of Automation (LoA) classification system is the SAE (Society of Automotive Engineers), which specifies five Automation Levels. This emphasises division of authority between the driver and the system – the highest level is reached by a vehicle which can autonomously navigate under all circumstances, and is in no need of any form of human supervision (Sousa et al., 2018).

The vehicle currently at the most advanced level of automation accessible to the public is Waymo's Level 4 driverless car (according to the SAE's classification system, Ackerman, 2021), currently capable of operating in a geofenced area of Phoenix, AZ under ideal weather conditions. This vehicle is supervised by so-called "remote operators" (Matousek, 2019; Hawkins, 2020), whose job involves intervening in scenarios where the vehicle is faced with an uncertain or novel scenario. As there will ultimately be no need for passengers to take control of these vehicles, lobbying efforts are already underway by industry participants to remove regulations requiring the inclusion of traditional control elements such as pedals and steering wheels from autonomous vehicles (Hawkins, 2019). While currently no vehicle can be described as having reached full automation under all circumstances according to the Society of Automotive Engineers (SAE, 2014) or National Highway Traffic Safety Administration (NHTSA, 2013) frameworks, most industry observers agree that eventually progressing to the highest level of automation is only a matter of time. We are currently in an age where varying levels of human-supervised autonomous vehicles share the road with traditional vehicles, and the proportion of autonomous vehicles is expected to increase (Rahman et al, 2021). However, while technology develops enough for Level 5 automation to become widespread, there will be a time period where varying levels of human-supervised autonomous vehicles share the road with traditional vehicles (Martínez-Díaz & Soriguera, 2018). Sparrow and Howard (2017) argue that autonomous vehicles relying on human supervision or intervention to any degree will prove a safety risk when used at a large enough scale by the driving public. Merat et al. (2014) report in a driving simulation experiment that on average a driver takes 15 seconds to regain control of a vehicle, with up to 40 seconds to stabilize control – expecting drivers or remote operators to take over a vehicle in a dangerous scenario given these response times is not without risks (Mirnig et al., 2017). Similarly, remote human supervision (as in the case of Waymo or Cruise at the present moment) may not be economically feasible with widespread adoption of vehicles at Level 4 automation. Some researchers go even further, and propose eventually banning manual driving, once reliable-enough Level 5 automation has been established (Müller & Gogoll, 2020; Sparrow & Howard, 2017). It seems that the industry is headed to full automation without any human supervision in the medium- to long-term future, driven by technological developments, economic incentives and ethical considerations. Even though such developments are still in the future, how people currently feel about their risks and benefits now might be indicative of future readiness to adopt these technologies and whether the timeline to adoption will be shorter or longer (Davis et al., 1989). This is especially important, as studies tend to find that lower levels of vehicle automation are still more readily accepted than higher levels (Gopinath & Narayanamurthy, 2022).

Understanding what drives people's current level of comfort with decreasing (or eventually losing) third-party human supervision in autonomous vehicles would go a long way towards devising effective public communication- and information campaigns when the time comes to transition to Level 5 automation (Walker & Marchau, 2017; Bögel et al., 2018). Similarly, being able to characterize attitudes on a higher, macro-level can help inform policymakers when targeting communication strategies on a national level.

We start the present study by surveying previous findings on the determinants of attitudes towards self-driving in general, and literature on individuals' preference for human involvement when it comes to automated decision processes. We derive our research questions from this existing literature.

Previous research on comfort with self-driving vehicles

Understanding people's level of comfort with autonomous vehicles has generated a considerable body of research over the past years (Gkartzonikas & Gkritza, 2019; Alawadhi et al., 2020). While there is no uniform definition for comfort, we focus on psychological comfort, the degree to which a technology user is at ease with using a technology (in comparison to say, ergonomic comfort, which has also been investigated in the AV literature; e.g. Paddeu et al., 2020). Comfort with technology has been previously investigated in the context of technology adoption and is examined through various attitudinal indicators, including perceived compatibility with lifestyle (Bove & Conklin, 2019), willingness to purchase (Young & Monroe, 2019), behavioural intention to use the technology (Czaja et al, 2006), and actual use behaviours (Ellis et al, 2021). In a general sense, level of comfort can be seen as the level to which a person will accept the technology in their everyday life (Nguyen et al, 2017), and is expected to be predictive of an individual's intention to use a technology (Fox & Connolly, 2018).

A number of individual characteristics have been found to be associated with attitudes towards using vehicles at various levels of autonomy, and have been the subject of considerable previous research (Haboucha et al., 2017; Becker & Axhausen, 2017). When it comes to gender differences, Bansal et al. (2016) find women have a lower willingness than men to pay for higher levels of automation, similarly to Pettigrew et al. (2018) and Sener et al. (2019). However, Rödel et al. (2014) find no gender difference in attitudes towards higher levels of autonomy. Kyriakidis et al. (2015) find no consistent gender effect in a large-scale survey when it comes to attitudes, although men do show a higher willingness to pay for automation. Hohenberger, Spörrle, & Welpe (2016) report gender differences in willingness to use autonomous vehicles – they explain this by the mediating effect of affective responses, where men are more likely to associate positive emotions with AVs. Higher age of exiting education, as a proxy of higher level of educational attainment overall, has been found to be a positive predictor for attitudes towards self-driving cars and trucks (Hudson et al., 2019). However, this finding might be partially due to a cohort effect, where older respondents also report lower educational attainment in most EU countries (Eurostat, 2020). Indeed, a common finding is that older individuals show more negative attitudes towards autonomous vehicles, and exhibit lower behavioral intentions to use (Rahman et al., 2019; Brechin et al., 2017). Kyriakidis et al. (2015) find that age correlates positively with worries about safety, and they report that older individuals are less comfortable without the presence of a wheel in an autonomous vehicle. Bansal et al. (2016) document lower willingness to pay for higher levels of automation in older individuals, similarly to Sener et al. (2019). In a nationwide US survey, Owens et al. (2015) found older respondents to be less enthusiastic for advanced vehicle technologies. Hulse et al. (2018) also find that younger and male individuals have a more positive perception of autonomous vehicles, and Hudson et al. (2019) report significant age and gender effects in the 2014 Eurobarometer data on attitudes about autonomous vehicles. Similarly, Pettigrew et al. (2018) find that individuals above 60 years of age exhibit more negative attitudes towards self-driving cars. This is in spite of those over 60 being more likely to experience medical conditions that could preclude them from driving. The potential benefits in mobility caused by the widespread adoption of autonomous vehicles for those living with a disability or medical conditions are significant (Fortunati et al., 2019; Cavoli et al., 2017; Harper et al., 2016). However, currently there is no consensus on how those living with a disability view autonomous vehicles. Zmud et al. (2016) find a small but significant positive effect on intent to use autonomous vehicles once they become available. The relative lack of evidence from previous studies regarding differences between able-bodied and disabled individuals might be due to the low prevalence of individuals with disabilities in the general population, yielding low statistical power when analyzing a representative sample (Alkhalaf & Zumbo, 2017). This low statistical power would be exacerbated by the correlation of old age and disability (United Nations, 2015).

Potential privacy risks (such as data sharing) have been suggested as a possible cause of low comfort and trust with AVs (Zavvos et al., 2021; Nguyen et al., 2022). Findings again have been mixed, with some studies finding effects of perceived privacy and security risks and others no effect (cf. Gurumurthy & Kockelman, 2020; Kaur & Rampersad, 2018). These differences may be caused by the framing of the privacy risks, for example, whether the rider's data is used for traffic coordination, law enforcement, or for targeted advertising.

Across all of these surveyed studies, the age-related decrease in comfort with AVs is the most stable. In comparison, the effects of gender, disability, and privacy risks are not consistent and require further study. One possible explanation for the contradictory findings across the literature could be that they are run in different countries with diverse cultures and norms. Gopinath and Narayanamurthy (2022) performed a meta-analysis of sixty-five studies on behavioural intention to use AVs. By dividing study populations into "Eastern" or "Western" cultures, they found a moderating impact of culture on the links between ease of use, attitudes, motivations, and behavioural intentions. They also found partial evidence for a moderating effect of level of automation on the links between perceived usefulness, trust, attitudes, ease of use, and behavioural intention to use AVs, where larger effect sizes tended to be found for SAE Levels 4 (high automation) and 5 (full automation) than for Level 3 (conditional automation). Differences in automation level, and in particular, the perceived loss of human supervision over the vehicle, may again explain the contradictory findings in the literature.

Preference for human decision-makers

There are several studies showing that increasing levels of automation are associated with increasingly negative attitudes and behavioral intentions for adoption (Kamalanathsharma et al, 2015). As Rödel et al. (2014) and Hewitt et al. (2019) report, with increasing levels of automation (progressing along the SAE classification system from 0 through 5), anxiety with using an autonomous vehicle increases, and perceived safety diminishes. This is especially the case when it comes to the transition from Level 4 (requiring supervision) to Level 5 (unsupervised).

Importantly, these previous studies follow the SAE's previously existing system for categorizing the level of automation a vehicle exhibits (SAE, 2014), without taking into account the potential presence or absence of third-party human supervision in each scenario. As all currently circulating autonomous vehicles either have a human operator physically present in the car, or one remotely supervising and intervening when necessary, understanding how the presence of third-party human supervision (or lack thereof) influences potential passengers' comfort with using an autonomous vehicle is essential to anticipate acceptance. Given the fact that Level 4 autonomy with remote human supervision is presently the most advanced use case at the forefront of AV development, and future developments will with a high likelihood bring fully autonomous cars lacking supervision by third parties, it is especially worthwhile to investigate what happens to consumer attitudes when external human supervision goes away completely. And more importantly, what are the individual-level determinants of comfort with such a scenario?

Outside the automotive context, Dietvorst et al. (2018) find that individuals prefer algorithms over which they can exert some control – a potential for including human influence on an algorithm's decision seems to put people at ease. There are a number of real-world applications where so-called human-in-the-loop systems are present (Nahavandi, 2017). In such scenarios a machine is working autonomously, while being supervised by a human operator who provides an input in case the machine is uncertain how to interpret a situation. The advanced driving frameworks by Alphabet subsidiary Waymo and GM subsidiary Cruise are further examples for such a system.

To summarize, people show a strong preference for involving humans in decision-making. This is also true when it comes to making decisions in the context of driving. In addition, as we have seen in our previous literature review on the individual correlates and attitudes towards AVs, people's comfort with being a passenger in an autonomous vehicle can be at least partially explained by their individual characteristics, but the findings in the literature have been contradictory. The previous studies, which have relied on a variety of designs, such as observational and experimental, have provided valuable insights into how AVs may be perceived by their prospective users. However, the range of approaches, questions, and contexts used make it difficult to identify why conflicting evidence has been found. Our approach is to use international survey data where the same set of questions have been given to a large population across different countries, and in three differing supervision contexts. By examining predictors of comfort with AVs through the lens of decreasing human supervision, we may be able to resolve the conflicting evidence from previous studies.

The present study

We use a pre-existing dataset, the Eurobarometer survey data (European Commission, 2020), collected during September 2019 ($n = 27565$), to examine comfort with automated vehicles. As previous literature shows contradictory findings, we examine the data through two lenses, by *country* and by *level of human supervision* in an attempt to identify commonalities and patterns in the results.

Our main research questions are as follows:

(1) What are people's attitudes towards fully automated vehicles at different levels of third-party human supervision?
(2) What are the individual-level predictors for comfort at different levels of supervision?
(3) Does the importance of previously identified predictors for comfort with autonomous vehicles change, depending on the level of third-party human supervision present?

Data

The Eurobarometer is a cross-sectional dataset containing information on individual demographic characteristics, and attitudes towards autonomous vehicles and other relevant variables. The data was collected in-person by trained interviewers in the respondent's household and is freely available for purposes of academic research. The Eurobarometer covers all current member states of the European Union at the time of data collection. About one thousand randomly selected individuals (ages 15 and older) were contacted by Kantar Public in most countries, with approximately 1500 in Germany, and 500 each in Cyprus, Malta and Luxembourg. The survey is representative on the level of individual countries. The three questions included in the survey which constitute our dependent variables are framed as seen in Table 1. These questions examine comfort with travelling in a fully automated vehicle under three levels of third-party human supervision. Before these questions were asked, participants were instructed "Now we would like to ask you some questions about automated vehicles. Automated vehicles are vehicles that will drive themselves (also referred to as fully automated or self-driven vehicles). They will not require intervention of a human user. It will still be a few years before fully automated vehicles appear on our roads, though today many vehicles have already advanced driver assistance functions.". Participants were then shown three images of automated vehicles: a shuttlebus, a personal car, and a truck, and asked to what extent each image matched with their personal understanding of an automated vehicle (European Commission, 2020). The participants were then asked the three questions about comfort with automated vehicles under differing levels of human supervision. The similarity of wording of the three survey questions that were chosen for our dependent variables allows us to investigate changing influences when it comes to systematically decreasing levels of third-party human supervision in a fully automated scenario.

Methods

Following our research questions, we examine our data set in three systematic analyses, increasing in computational complexity, with descriptive, regression, and ordinal random forest approaches.

To investigate RQ 1, responses to the three questions were first examined through a descriptive analysis. We first measured the proportion of comfort responses (five categories, comfort ratings ranging from "*Not at all comfortable*" to "*Totally comfortable*", after "*Don't know*" and NA responses were removed) to the three levels of human supervision. We then examined the mean level of comfort in a *level of human supervision* $\times$ *country* analysis, using bootstrapping to calculate confidence intervals by country. Differences between the three levels of human supervision by country were examined using Fisher's exact tests.

We then constructed three ordered logistic regression models to analyse individual responses to the three levels of human supervision for RQ 2. We selected a wide range of predictors to include in our models, guided by previous literature. In addition to country, demographic variables which have been found in past research to be predictive of attitudes towards self-driving vehicles, and were available to us in the data set were included. These variables included age, gender, marital status, age of finishing education, occupation, internet and telephone use. In addition, we included a number of attitudinal measures from the original survey, which were also expected to be predictive of comfort with autonomous driving at different levels of human supervision. These measures include for example, items surveying comfort with sharing data with other

Table 1
Distribution of dependent variables.

		Level	N	%
To what extent would you feel comfortable or not travelling in a fully automated vehicle under the following conditions:	With the supervision of a human operator in the vehicle	Totally comfortable	9223	33.5
		Fairly comfortable	9988	36.2
		Not very comfortable	3976	14.4
		Not at all comfortable	3669	13.3
		Don't know / NA	709	2.6
	With the remote supervision of a human operator	Totally comfortable	2855	10.4
		Fairly comfortable	7219	26.2
		Not very comfortable	8706	31.6
		Not at all comfortable	7997	29
		Don't know / NA	788	2.9
	Without the supervision of a human operator	Totally comfortable	1815	6.6
		Fairly comfortable	4200	15.2
		Not very comfortable	7240	26.3
		Not at all comfortable	13,406	48.6
		Don't know / NA	904	3.3

road users, governments or private companies (for a full list of predictors with their respective levels, see Supplementary Table 1). All effects were dummy coded, where coefficients were compared to the reference level of each predictor. Coefficients indicate odds ratios. We report log-likelihood, AIC, and BIC for each regression as estimators of model fit. All statistical tests were two-sided, with $p < 0.05$ considered as statistically significant.

Finally, in order to better understand the drivers of comfort ratings across varying levels of human supervision and whether these predictors change in importance (RQ 3), we constructed three ordinal random forest models (Hornung, 2020). Similar to our earlier regressions, our approach respects the ordinality of our dependent variables – not assuming equal distance between answer options as an ordinary least squares approach would, while still retaining the hierarchical nature of the answer options. This analysis does not rely on stringent model assumptions due to its nonparametric nature, while also being less prone to be influenced by multicollinearity. Furthermore, due to the iterative nature of the algorithm, it is able to account for interactions without including previously specified interaction effects. Most importantly, this method provides a permutation variable importance metric to quantify the overall influence certain variables have in a model, and which then enables us to compare how this influence changes from one model to the next (in our case from dependent variable to dependent variable). Interpreting changes in variable importance provides valuable insight into how the effect of various predictors (for example gender, or having a driver's license) might have a different effect on one's comfort rating, depending on the level of third-party human supervision present. Our models were fitted using default hyperparameters, as they were all in a suitable range for the size and complexity of our dataset (Hornung, 2020). One downside of random forest models is that the time required to fit them increases exponentially with the complexity of the dataset. As one of our key predictor variables (*Country*) has 28 levels, iterating through each value and selectively including them or not including them would lead to a large computational burden, and ultimately would not reflect the role of country-differences in our dataset accurately. One-hot encoding a variable with 28 values runs into similar constraints. In order to address this issue, we first collapsed our complete dataset into 4 factors (as suggested by a scree-plot) using Multiple Correspondence Analysis (Kassambara & Mundt, 2017; Le, Josse, & Husson, 2008). This method is conceptually similar to principal component analysis, but it needs categorical data (which we have) to reduce dimensionality. After generating factor scores for each individual, we aggregated these scores by country, to represent country-level variability in our models without having to include 28 additional variables. Following this, we performed k-means clustering, in order to create 5 clusters of countries, based on their similarity to each other in our dataset. The resulting permutation variable importance rankings for each model enabled us to visualize and interpret the changing role variables such as age, gender etc. play across our three models. However, this analysis does not allow us to interpret country-level uniqueness. The five clusters of countries were examined for possible similarities with other objective groupings (e.g. by region, by culture, by language family, by latitude), but no similarities were found. Therefore, country cluster should not be interpreted in this analysis. To resolve this lack of interpretability, we performed an exploratory linear model, including all the previous predictors from the earlier regressions, and including three-way interaction terms for the three most important predictors by country and by level of human supervision.

Results

Attitudes at different levels of third-party human supervision

When examining the distribution of responses from question to question with decreasing levels of human supervision (“*Comfort with in-car human supervision*”, “*Comfort with remote human supervision*”, and “*Comfort with no human supervision*”), we observe a trend of decreasing comfort ratings. While 33.5 % are totally comfortable with being a passenger in the physical presence of a human operator, this value decreases to 10.4 % when it comes to remote supervision, and further to 6.6 % in the case of no human supervision. (Table 1.).

Interestingly, we observe that this shift in individual attitudes is not monotonous. We find that a number of individuals exhibit more positive attitudes towards remote supervision compared to in-car human supervision (Fig. 1.). Similarly, a smaller number of individuals prefer full autonomy to supervised options. Our survey dataset enables us to characterize individuals who react to decreasing third-party human supervision with increasing comfort ratings. There are three countries where this response pattern is two-to-three times more common than in the median country: Romania, Hungary and Poland give 24 % of those who prefer less supervision at some point to more supervision, while constituting only 10.8 % of the complete sample. Fisher’s exact tests show that the distribution of respondents who either prefer remote human supervision to in-car supervision ($p < 0.001$) or who prefer no third-party human supervision to remote supervision ($p < 0.001$) is significantly related to country of origin.

At a higher level of aggregation (on the level of countries), we find that samples in various member states have divergent views on human supervision of autonomous vehicles. Some Nordic countries such as Sweden, Denmark and Finland overall show higher comfort with in-car human supervision and remote supervision than most other countries, while Eastern-European countries such as Poland and Romania are also relatively comfortable with remote supervision (Fig. 2 – in all plots and analyses higher values indicate higher comfort ratings). However, when it comes to unsupervised self-driving vehicles, comfort in Nordic countries for example drops considerably below that of Eastern European countries. A further interesting case is that of the Netherlands, where respondents are some of the most open to in-car supervision, while they are among the least comfortable with no third-party human supervision. In order to understand what might be contributing to these observed shifts in comfort, and how these effects might be different depending on the level of human supervision at hand, we implement three ordinal logistic regression models, predicting our three dependent variables separately.

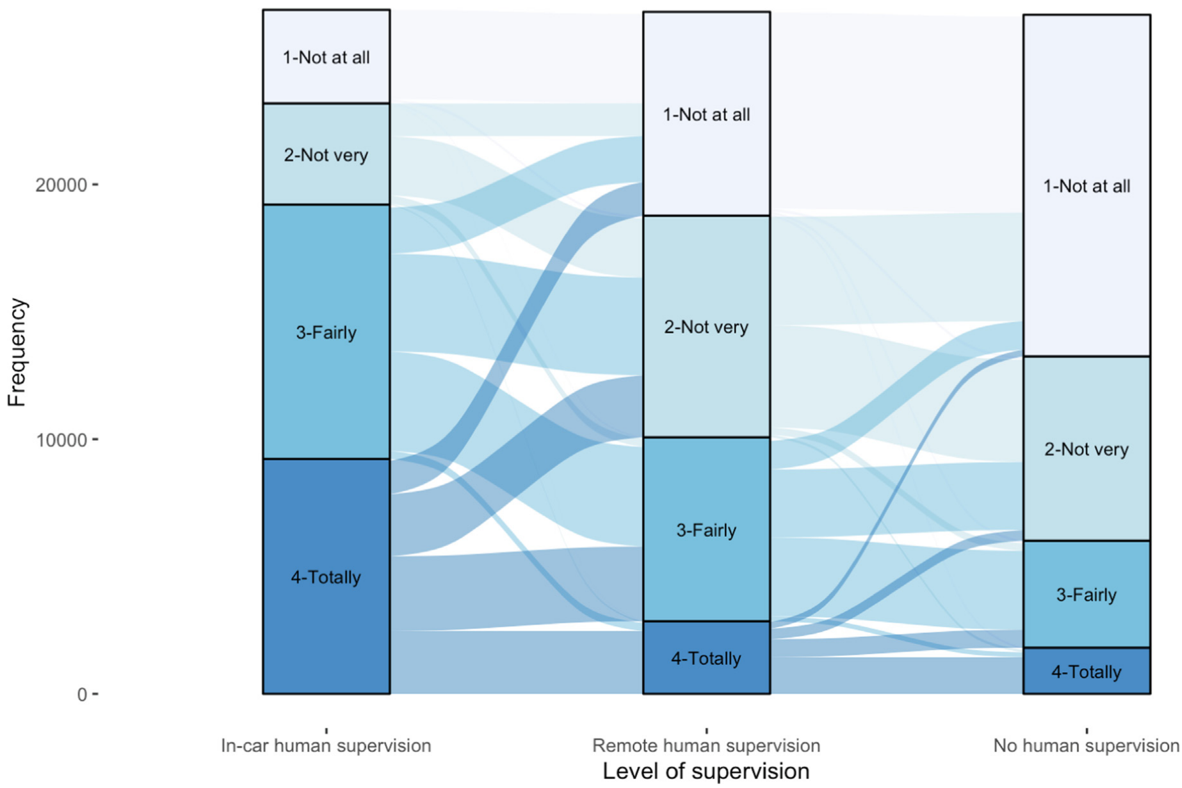

Fig. 1. Alluvial plot for comfort across three levels of third-party human supervision. The flow of responses from the highest level of third-party human supervision (In-car human supervision), to the lowest level (No human supervision).

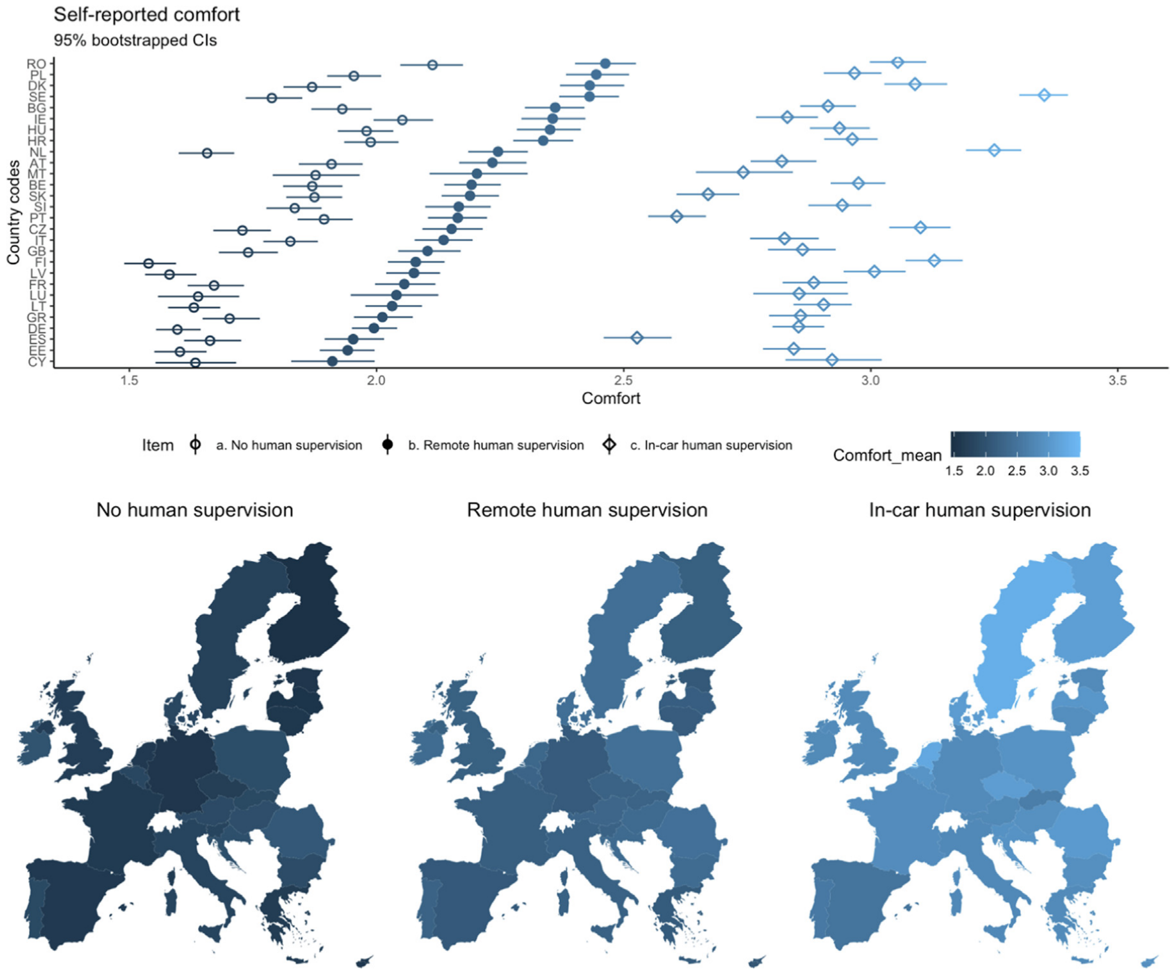

Fig. 2. Changes in comfort with varying levels of third-party human supervision. Country means and bootstrapped confidence intervals for each of our three dependent variables. Higher values on the x-axis indicate higher self-reported comfort. Dot plot ordered by "Remote human supervision". Mean comfort values are calculated after assigning a numerical value to the available answer options as follows: 1 – Not at all comfortable; 2 – Not very comfortable; 3 – Fairly comfortable; 4 – Totally comfortable.

Individual-level predictors of comfort

Table 2. contains detailed information on the three regression models (for the model table with all predictors, see Supplementary Table 2). What immediately becomes clear when surveying our three regression models is the key role attitudes towards sharing data with third parties play in predicting one's comfort with different self-driving scenarios. Self-reported level of comfort with sharing data with other road users, one's government and private companies is predictive of comfort level with AVs. Individuals who are more comfortable with data sharing are more comfortable with using self-driving vehicles at all levels of supervision.

In line with some of the previous literature, we document a significant effect of gender on comfort with being a passenger in a fully autonomous vehicle. Males reported being significantly more comfortable, independently of the level of third-party human supervision present. When comparing the coefficient estimates across our regression models, we find a growing gender gap with decreasing third-party human supervision.

When it comes to education, we find that individuals who exited the education system at age 18 or before tended to be substantially less open to traveling in an autonomous vehicle, while those who ended their education at the age of 21 or older, or who were still studying were significantly more comfortable in all models. Those who were still studying were significantly more comfortable with AVs than those who had ended their education, in both the in-car supervised and remote supervised scenarios. In line with this, for age we find that younger respondents were more comfortable with AVs, independently of the level of third-party human supervision present. Those who were 65 years or older were significantly less comfortable with all levels of supervision. Similarly, respondents living with a disability or having reduced mobility were significantly less comfortable with in-car or remote supervision, although this effect was not present with AVs with no supervision.

Table 2
Ordinal logistic regression models. Standard errors clustered by countries.

		In-car supervision	Remote supervision	No supervision
Gender	Female	1 (–)	1 (–)	1 (–)
	Male	1.118 ** (0.105)	1.388 *** (0.135)	1.728 *** (0.254)
Age	15–24	1.262 ** (0.313)	1.695 *** (0.396)	1.755 *** (0.401)
	25–34	1.366 *** (0.236)	1.501 *** (0.286)	1.488 *** (0.305)
	35–44	1.272 *** (0.188)	1.368 *** (0.170)	1.487 *** (0.252)
	45–54	1.250 *** (0.147)	1.338 *** (0.175)	1.377 *** (0.211)
	55–64	1.232 *** (0.144)	1.205 *** (0.159)	1.182 ** (0.172)
	65 years and older	1 (–)	1 (–)	1 (–)
Education ended at age	No full-time education	0.616 *** (0.147)	0.836 (0.342)	0.964 (0.380)
	14 years or earlier	0.680 *** (0.130)	0.592 *** (0.108)	0.710 *** (0.200)
	15	0.698 *** (0.162)	0.700 *** (0.155)	0.757 ** (0.185)
	16	0.773 *** (0.120)	0.695 *** (0.098)	0.767 ** (0.185)
	17	0.859 ** (0.123)	0.727 *** (0.103)	0.753 *** (0.145)
	18	0.873 ** (0.106)	0.793 *** (0.073)	0.875 ** (0.102)
	19	0.847 *** (0.102)	0.826 *** (0.097)	0.940 (0.117)
	20	0.843 ** (0.142)	0.849 ** (0.122)	0.854 * (0.174)
	21	0.920 (0.181)	0.910 (0.135)	0.897 (0.170)
	22+	1 (–)	1 (–)	1 (–)
	Still studying	1.227 * (0.323)	1.201 * (0.248)	1.103 (0.237)
	DK	0.895 (0.336)	0.849 (0.272)	0.958 (0.352)
	Refusal	0.886 (0.866)	0.939 (0.788)	1.617 * (0.953)
Phone	Landline and Mobile	1 (–)	1 (–)	1 (–)
	Mobile only	0.949 (0.089)	1.093 ** (0.092)	1.103 ** (0.091)
	Landline only	0.603 *** (0.224)	0.846 (0.213)	0.952 (0.241)
	No telephone	0.757 ** (0.187)	0.917 (0.257)	1.127 (0.289)
Internet use index	Every day / almost every day	1 (–)	1 (–)	1 (–)
	Two or three times a week	0.763 *** (0.151)	0.819 *** (0.132)	0.888 (0.154)
	Once a week	0.723 ** (0.207)	0.817 * (0.220)	1.000 (0.252)
	Two or three times a month	0.543 ** (0.342)	0.646 * (0.369)	0.883 (0.575)
	Less often	0.874 (0.240)	1.043 (0.327)	1.267 * (0.348)
	Never	0.707 *** (0.116)	0.767 *** (0.115)	0.856 ** (0.136)
	No access	0.738 * (0.263)	0.671 ** (0.251)	0.764 (0.334)
Community size	City or large urban area	1 (–)	1 (–)	1 (–)
	Towns and suburbs or small urban area	0.951 (0.118)	0.870 *** (0.084)	0.867 * (0.132)
	Rural area	0.916 (0.123)	0.815 *** (0.102)	0.808 *** (0.142)
Reduced mobility or disability	No	1 (–)	1 (–)	1 (–)
	Yes	0.836 *** (0.117)	0.889 ** (0.106)	0.928 (0.106)
Heard about AV within last 12 months	No	1 (–)	1 (–)	1 (–)
	Yes	1.580 *** (0.204)	1.246 *** (0.172)	1.034 (0.148)
	DK	0.979 (0.332)	1.049 (0.472)	1.251 (0.514)
Sharing data, road users	Totally comfortable	1 (–)	1 (–)	1 (–)
	Fairly comfortable	0.641 *** (0.099)	0.690 *** (0.149)	0.689 *** (0.152)
	Not very comfortable	0.525 *** (0.105)	0.489 *** (0.150)	0.475 *** (0.147)
	Not at all comfortable	0.425 *** (0.117)	0.319 *** (0.131)	0.300 *** (0.161)
	DK	0.606 *** (0.206)	0.591 *** (0.267)	0.511 *** (0.235)
Sharing data, private companies	Totally comfortable	1 (–)	1 (–)	1 (–)
	Fairly comfortable	0.819 ** (0.174)	0.691 *** (0.149)	0.677 *** (0.162)
	Not very comfortable	0.824 * (0.202)	0.517 *** (0.138)	0.476 *** (0.181)
	Not at all comfortable	0.870 (0.226)	0.365 *** (0.151)	0.285 *** (0.192)
	DK	0.913 (0.330)	0.479 *** (0.191)	0.397 *** (0.238)
Sharing data, public authorities	Totally comfortable	1 (–)	1 (–)	1 (–)
	Fairly comfortable	0.628 *** (0.131)	0.818 ** (0.156)	0.907 (0.189)
	Not very comfortable	0.428 *** (0.140)	0.585 *** (0.177)	0.761 ** (0.214)
	Not at all comfortable	0.288 *** (0.147)	0.386 *** (0.152)	0.597 *** (0.229)
	DK	0.321 *** (0.204)	0.418 *** (0.230)	0.661 ** (0.249)
	logLik	−31637.307	−30701.95	−27373.193
	AIC	63,441	61,570	54,912
	BIC	64,121	62,250	55,592
	n	26,846	26,768	26,652

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Models controlled for: Country, Marital status, Occupation, Driving license.

Those living in cities were more favorable towards AVs with remote or no supervision than those living in smaller towns or the countryside. Mobile phone access seems to have substantial predictive power in comparison to landline access as third-party human supervision is reduced, such that those with only mobile phone access are significantly more comfortable with AVs in the second two models. Frequency of Internet use overall predicts comfort in our first two models, and those who never use the internet are significantly less comfortable with all three levels of automation. Variables such as internet use and phone access are most likely proxies for an interest or capacity to keep up with technological developments. Our respondents were also asked if they recall having heard of autonomous vehicles over the past 12 months. This variable had a significant effect in the first and second models, and no significant effect in the third model. While having heard of AVs recently positively influences people's comfort with traveling in an AV with human supervision, it has no effect on comfort with no human supervision. When observing the odds ratios for country effects in our regression (Supplementary Table 2), we find a similar pattern to our earlier descriptive analyses – the positive effect from countries such as Sweden, Finland and the Netherlands drop considerably in Models 2 and 3, while the effect from Romania and Poland increases with reduction in human supervision.

Results from permutation variable importance

Fig. 3 depicts variable importance rankings from our random forest models. The random forest approach provides a very similar overall picture to the regression approach when it comes to the effect of individual variables, which serves as an additional validation of our regression models. The importance of data privacy is highlighted by our variable importance measure, where these are consistently among the variables with the highest importance. Interestingly, we find that sharing data with private companies becomes more important from Model 1 to Model 3, increasing from sixth in Model 1 to the most important variable in Model 3.

In line with the increasing gender gap across our regression models, our variable importance rankings show that the effect of gender increases substantially across our three random forest models. While gender has low variable importance when it comes to predicting comfort with in-car human supervision (Model 1), it becomes one of the more important variables when it comes to predicting comfort with remote human supervision (Model 2) and finally emerges as the fifth most important variable in Model 3, predicting comfort with unsupervised driving.

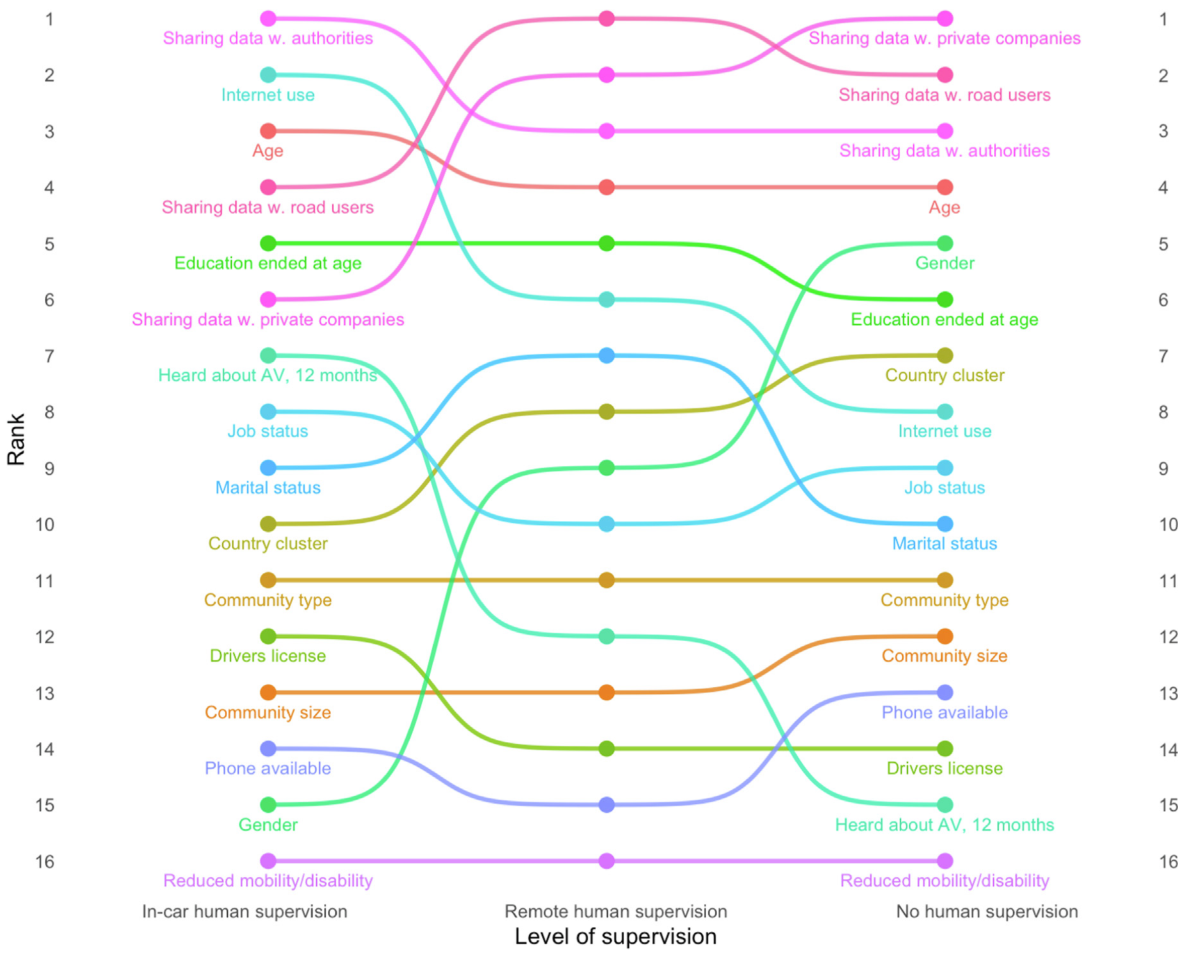

Fig. 3. Permutation variable importance of predictors with decreasing third-party human supervision. Variables presented in descending order of variable importance.

We find respondent age to be consistently one of the most important variables in all three random forest models, starting at third place and dropping to fourth. This again matches the results from the regression models. This is also mirrored by age leaving education, which drops from fifth to sixth place across the models. In comparison, disability is the lowest ranked variable across all of our models.

While our regression models showed that phone access seems to have substantial predictive power at higher levels of third-party human supervision (such that those with mobile phone access are significantly more comfortable with AVs), our importance ranking shows this variable to not contribute much to our models. Internet use, which starts as the second most important variable in Model 1, declines in contribution substantially to eighth in Model 3. Similarly, while having heard about AVs in the past 12 months is ranked seventh in Model 1, the importance ranking of this variable decreases consistently from Model 1 to Model 3 to become the second lowest ranked. It seems that previous knowledge of autonomous vehicles only affects one's attitudes towards actually traveling in one if there is a human in the loop – when this element is not the case, one's level of previous information does not seem to make a difference.

Our variable importance ranking shows a slight increase in the importance of our country cluster variable from Model 1 to Model 3. However we cannot interpret this, as the country clusters do not map onto other objective groupings. We took the three data privacy measures (as the predictors with highest variable importance in our last model) for our exploratory linear regression analysis (supplementary Figs. 1, 2, & 3, full regression table can be found in the supplementary data file). From this, we can see that in general, as comfort with sharing data increases, comfort with AVs also increases. In the case of no human supervision, this effect is particularly pronounced for Malta when sharing data with road users, and Portugal when sharing data with private companies.

Discussion & conclusion

Overall, we have documented that respondents to the Eurobarometer survey are less comfortable with lower levels of third-party human supervision in a fully autonomous vehicle. While there is considerable heterogeneity in how individuals responded to these three questions, the overall negative trajectory is very clear. When it comes to country effects, we find both in our descriptive as well as our regression analyses that there are marked differences on a national level – not just within each individual model, but also from one model to the next. This implies that the dynamics of how comfortable inhabitants of different countries are with varying levels of human supervision can be quite different. These country effects are robust when accounting for a large number of individual characteristics. This heterogeneity should inform those trying to shape policy and approaches to communication in a European context when it comes to the future of autonomous vehicles – while ultimately there is a need for a harmonized framework across the EU when it comes to these issues, a one-size-fits all approach seems challenging in the face of such a diversity of attitudes. In addition, further study of cultural aspects when it comes to acceptance of unsupervised self-driving technologies is called for in the future. For some countries, comfort with AVs increased with decreasing third-party supervision. This pattern can be interpreted as follows: while there seems to be a general aversion to decreasing third-party supervision, for a substantial number of respondents in some countries, lower levels of human supervision are associated with higher comfort ratings. While it is beyond the scope of the present paper to investigate the underlying cause of such preferences in depth, a potential explanation could be lower interpersonal trust levels in some of these countries (Inglehart and Welzel, 2010; Pellegrini et al., 2021).

When it comes to individual characteristics, our findings are largely in line with existing literature (c.f. Haboucha et al., 2017; Becker & Axhausen, 2017; Bansal et al., 2016; Sener et al., 2019). Younger, male and more educated individuals would be more comfortable overall with traveling in a fully autonomous vehicle. We find that level of education plays a similarly important role across all models: individuals who spent more time in formal education are in general more comfortable with self-driving at all levels of supervision. While effects of age and education are consistent across the previous literature, our analysis allows us to draw conclusions about conflicting studies for other variables. When controlling for age, we find a negative effect of reduced mobility / disability on comfort with AVs (although this variable does not have a high importance in our subsequent analysis). Our findings are in contrast to Zmud et al's (2016) findings where a small positive effect was found.

We additionally find that the effect of gender depends on the level of human supervision present to a large extent. Female respondents become substantially less comfortable than males with being in a fully automated vehicle when in-car human supervision is replaced by remote human supervision. A further shift to complete lack of external human supervision drives an even larger deviation in comfort. This finding might help explain some previously described contradictory findings in the literature when it comes to gender as predictors for AV acceptance (Hohenberger et al., 2016; Rödel et al., 2014). It seems that the effect of gender on attitudes towards travelling in autonomous vehicles is moderated by the level of third-party human supervision present.

In what might be a phenomenon unique to a European context, we find that some of the strongest and most consistent predictors of comfort with being a passenger in a self-driving car is comfort with sharing data with other road users, authorities and private companies. Brell et al. (2019) similarly find in a survey with 516 German respondents that potential users of autonomous vehicles have concerns regarding how their personal data is handled in such a setting – furthermore, these concerns are not abated by increased experience, as is the case for other perceived risks. This is in accordance with the overall high importance placed on data privacy present in Europe (with considerable heterogeneity in attitudes and practices across member states, Lusoli et al., 2012). These observations highlight the need for transparent regulation and communication when it comes to the user data AV operators have access to, and how this is shared with governments and other road users. We also document that the importance of attitudes towards sharing data with private companies increases with lower supervision. In our final exploratory analysis, we identified that Malta (when sharing data with road users), and Portugal (when sharing data with private companies) showed strong effects of comfort with data sharing when considering AVs with no human supervision. This suggests that for these countries, public information campaigns that emphasise data security and transparency would be particularly important when attempting to increase public acceptance of AVs.

A possible explanation for our overall result of decreasing comfort with increasing levels of automation may come from attitudes to machines making decisions with moral implications (Awad et al., 2018; Awad et al., 2020a). Previous literature on the permissibility of letting machines make life-or-death decisions in a driving context shows that people have strong preferences for human involvement (Bigman & Gray, 2018) – participants overwhelmingly prefer that humans make such decisions, even when they are informed that the algorithm shows superior performance (Castelo et al., 2019). Additionally, recent findings on assigning blame to a human passenger or to a self-driving car when someone is harmed shows that most of the blame still falls on the passenger/operator of an autonomous vehicle (Awad et al., 2020b). Given this dynamic, potential passengers' reluctance to get third-party human supervision (be it in-car or remote) out of the loop would be understandable.

While delivering interesting new insights, the current study is not without its limitations. Most importantly, it relies on a cross-sectional dataset, which does not enable us to establish the existence of causal relationships between our predictors and our dependent variables. The survey was conducted in mother tongue language in 28 countries, giving a possibility of variations in question phrasing between groups of respondents, and the understanding of what constitutes an Automated Vehicle (although it should be noted that the survey included three images of potential AVs – private car, shuttle bus, and truck). Furthermore, while the data is representative on the level of individual countries, certain segments of the public (for example those living with disability or reduced mobility) might still be underrepresented in terms of statistical power. Given the high level of economic and political integration in the European Union, and the diverse attitudes member states represent regarding a number of relevant issues including the acceptance of robots, or GMOs for example (Gnambs & Appel, 2019, Torgersen & Seifert, 1997), it is important to understand differences between member states. Additionally, identifying similarities across member states could aid policymaking and communication on an international level. Being able to characterize attitudinal differences and similarities when it comes to decreasing human supervision in automotive mobility on a country-level might contribute to tailoring AV policy and communication in a European context. Our study documents several differences between European countries. However, the nature of our study did not allow us to examine variable importance on a per-country basis. Finally, one might wonder about the hypothetical nature of our dependent variables, when there is currently no fully autonomous vehicle on the road without human supervision.

However, given the potentially transformative role such future developments will have, and the fact that attitudes towards the risks and benefits of technological innovation have been shown in a number of studies to predict their eventual acceptance (c.f. Porter & Donthu, 2006; Bögel et al., 2018), we believe the current formulation of our study is well-justified. While attitudes will most certainly change as technologies develop, having a baseline understanding of the various factors at play is essential. We hope that future research will delve deeper into the findings we document here.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank Sandra Andraszewicz for her comments and feedback on an early version of the manuscript, and Christoph Hoelscher for feedback and proofreading in the later stages.

The research was conducted at the Future Resilient Systems Programme at the Singapore-ETH Centre, which was established collaboratively between ETH Zurich and the National Research Foundation Singapore. This research is supported by the National Research Foundation Singapore (NRF) under its Campus for Research Excellence and Technological Enterprise (CREATE) programme, and the Donald C. Cooper-Fonds at ETH Zurich, Project No. ETH-08 17-1 (principal investigators C. Hoelscher and S. Andraszewicz).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijtst.2022.08.001.

References

Ackerman, E., 2021. What full autonomy means for the Waymo driver. IEEE Explore https://spectrum.ieee.org/cars-that-think/transportation/self-driving/full-autonomy-waymo-driver.

Administration, N.H.T.S. et al., 2013. Preliminary statement of policy concerning automated vehicles. Washington, DC. pp. 1–14.

Alawadhi, M., Almazrouie, J., Kamil, M., Khalil, K.A., 2020. A systematic literature review of the factors influencing the adoption of autonomous driving. Int. J. Syst. Assur. Eng. Manage., 1–18
Alkhalaf, A., Zumbo, B.D., 2017. The impact of predictor variable (s) with skewed cell probabilities on Wald tests in binary logistic regression. J. Modern Appl. Stat. Methods 16 (2), 4.
Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shari, A., Rahwan, I., 2018. The moral machine experiment. Nature 563 (7729), 59–64.
Awad, E., Dsouza, S., Shari, A., Rahwan, I., Bonnefon, J.-F., 2020a. Universals and variations in moral decisions made in 42 countries by 70,000 participants. Proc. Natl. Acad. Sci. 117 (5), 2332–2337.
Awad, E., Levine, S., Kleiman-Weiner, M., Dsouza, S., Tenenbaum, J.B., Shari, A., Rahwan, I., 2020b. Drivers are blamed more than their automated cars when both make mistakes. Nat. Hum. Behav. 4 (2), 134–143.
Badue, C., Guidolini, R., Carneiro, R.V., Azevedo, P., Cardoso, V.B., Forechi, A., et al, 2020. Self-driving cars: a survey. Expert Syst. Appl. 113816.
Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: an Austin perspective. Transport. Res. Part C: Emerg. Technol. 67, 1–14.
Becker, F., Axhausen, K.W., 2017. Literature review on surveys investigating the acceptance of automated vehicles. Transportation 44 (6), 1293–1306.
Bigman, Y.E., Gray, K., 2018. People are averse to machines making moral decisions. Cognition 181, 21–34.
Bögel, P., Oltra, C., Sala, R., Lores, M., Upham, P., Dütschke, E., et al, 2018. The role of attitudes in technology acceptance management: reflections on the case of hydrogen fuel cells in Europe. J. Clean. Prod. 188, 125–135. https://doi.org/10.1016/j.jclepro.2018.03.266.
Bove, L.A., Conklin, S., 2019. Using the technology adoption model to assess faculty comfort with the Learning Management System. Online J. Dist. Learn. Admin. 22 (3), n3.
Brechin, S., Farr, M., Hurley, J., King, P., Willis, N., 2017. Age and Safety Perceptions in Autonomous Vehicles. University of Christchurch, New Zealand.
Brell, T., Philipsen, R., Ziefle, M., 2019. sCARy! Risk perceptions in autonomous driving: the influence of experience on perceived benefits and barriers. Risk Anal. 39 (2), 342–357.
Castelo, N., Bos, M.W., Lehmann, D.R., 2019. Task-dependent algorithm aversion. J. Mark. Res. 56 (5), 809–825.
Cavoli, C., Phillips, B., Cohen, T., Jones, P., 2017. Social and behavioural questions associated with Automated Vehicles A Literature Review. UCL Transport Institute.
Chan, C.Y., 2017. Advancements, prospects, and impacts of automated driving systems. Int. J. Transp. Sci. Technol. 6 (3), 208–216.
Committee, S.-O.-R.-A.-V.-S. et al, 2014. Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. SAE Stand. J. 3016, 1–16.
Czaja, S.J., Charness, N., Fisk, A.D., Hertzog, C., Nair, S.N., Rogers, W.A., Sharit, J., 2006. Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). Psychol. Aging 21 (2), 333–352. https://doi.org/10.1037/0882-7974.21.2.333. PMID: 16768579; PMCID: PMC1524856.
Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1989. User acceptance of computer technology: a comparison of two theoretical models. Manage. Sci. 35 (8), 982–1003.
Dietvorst, B.J., Simmons, J.P., Massey, C., 2018. Overcoming algorithm aversion: people will use imperfect algorithms if they can (even slightly) modify them. Manage. Sci. 64 (3), 1155–1170.
Ellis, M.E., Downey, J.P., Chen, A.N., Lu, H.K., 2021. Why taiwanese seniors use technology. Asia Pacific Manage. Rev. 26 (3), 149–159.
European Commission, B., 2020. Eurobarometer 92.1 (2019). GESIS Datenarchiv, Köln. ZA7579 Datenfile Version 2.0.0. https://doi.org/10.4232/1.13541.
Eurostat, 2020. Level of educational attainment by age. Retrieved from: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Educational_attainment_statistics#Level_of_educational_attainment_by_age.
Fortunati, L., Lugano, G., Manganelli, A.M., 2019. European perceptions of autonomous and robotized cars. Int. J. Commun. 13, 2728–2747.
Fox, G., Connolly, R., 2018. Mobile health technology adoption across generations: Narrowing the digital divide. Inform. Syst. J. 28 (6), 995–1019.
Gkartzonikas, C., Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transport. Res. Part C: Emerg. Technol. 98, 323–337.
Gnambs, T., Appel, M., 2019. Are robots becoming unpopular? Changes in attitudes towards autonomous robotic systems in europe. Comput. Hum. Behav. 93, 53–61.
Gopinath, K., Narayanamurthy, G., 2022. Early bird catches the worm! Meta-analysis of autonomous vehicles adoption–Moderating role of automation level, ownership and culture. Int. J. Inf. Manage. 66, 102536.
Gurumurthy, K.M., Kockelman, K.M., 2020. Modeling Americans' autonomous vehicle preferences: a focus on dynamic ride-sharing, privacy & long-distance mode choices. Technol. Forecast. Soc. Chang. 150, 119792.
Inglehart, R., Welzel, C., 2010. Changing mass priorities: The link between modernization and democracy. Perspectives Politics 8 (2), 551–567.
Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transport. Res. Part C: Emerg. Technol. 78, 37–49.
Harper, C.D., Hendrickson, C.T., Mangones, S., Samaras, C., 2016. Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. Transport. Res. Part C: Emerg. Technol. 72, 1–9.
Hawkins, A.J., 2019. Self-driving carmakers urge regulators to whi the steering wheel out the window. Retrieved from https://www.theverge.com/2019/8/30/20840631/self- driving-carmakers-federal-safety-rules-nhtsa-steering-wheels-pedals-waymo-cruise.
Hawkins, A.J., 2020. Coronavirus shows there's still no such thing as a totally human-free self-driving car. Retrieved from https://www.theverge.com/2020/3/18/21183421/self-driving-cars-coronavirus-covid19-human-drivers-waymo-cruise-zoox.
Hewitt, C., Politis, I., Amanatidis, T., Sarkar, A., 2019. Assessing public perception of self-driving cars: the autonomous vehicle acceptance model. In: Proceedings of the 24th International Conference on Intelligent User Interfaces, pp. 518–527.
Hohenberger, C., Spörrle, M., Welpe, I.M., 2016. How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. Transport. Res. Part A: Policy Pract. 94, 374–385.
Hornung, R., 2020. OrdinalForest: Ordinal forests: Prediction and variable ranking with ordinal target variables. Retrieved from https://CRAN.R-project.org/package=ordinalForest.
Hudson, J., Orviska, M., Hunady, J., 2019. People's attitudes to autonomous vehicles. Transport. Res. Part A: Policy Pract. 121, 164–176.
Hulse, L.M., Xie, H., Galea, E.R., 2018. Perceptions of autonomous vehicles: relationships with road users, risk, gender and age. Saf. Sci. 102, 1–13.
Kamalanathsharma, R.K., Rakha, H.A., Zohdy, I.H., 2015. Survey on in-vehicle technology use: results and findings. Int. J. Transp. Sci. Technol. 4 (2), 135–149.
Kassambara, A., Mundt, F., 2017. Package 'factoextra'. In: Extract and Visualize the Results of Multivariate Data Analyses, p. 76.
Kaur, K., Rampersad, G., 2018. Trust in driverless cars: investigating key factors influencing the adoption of driverless cars. J. Eng. Tech. Manage. 48, 87–96.
Kyriakidis, M., Happee, R., de Winter, J.C., 2015. Public opinion on automated driving: results of an international questionnaire among 5000 respondents. Transport. Res. Part F: Trac. Psychol. Behav. 32, 127–140.
Le, S., Josse, J., Husson, F., 2008. FactoMineR: an R package for multivariate analysis. J. Stat. Softw. 25 (1), 1–18. https://doi.org/10.18637/jss.v025.i01.
Lusoli, W., Bacigalupo, M., Lupiáñez-Villanueva, F., Andrade, N.N.G.D., Monteleone, S., Maghiros, I., 2012. Pan-European survey of practices, attitudes and policy preferences as regards personal identity data management. In: JRC Scientific and Policy Reports, EUR, 25295.
Martínez-Díaz, M., Soriguera, F., 2018. Autonomous vehicles: theoretical and practical challenges. Transp. Res. Procedia 33, 275–282.
Matousek, M., 2019. Waymo is telling customers it will start oering rides in its autonomous cars without safety drivers. Retrieved from https://www.businessinsider.com/waymo-says-it-will-start-giving-rides-without- safety-drivers-2019-10?r=US&IR=T.
Merat, N., Jamson, A.H., Lai, F.C., Daly, M., Carsten, O.M., 2014. Transition to manual: driver behaviour when resuming control from a highly automated vehicle. Transport. Res. Part F: Trac. Psychol. Behav. 27, 274–282.

Mirnig, A.G., Stadler, S., Tscheligi, M., 2017. Handovers and resumption of control in semi-autonomous vehicles: what the automotive domain can learn from human-robot-interaction. In: Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-robot Interaction, pp. 207–208.
Mu̇ller, J.F., Gogoll, J., 2020. Should manual driving be (eventually) outlawed? Sci. Eng. Ethics, 1–19.
Nahavandi, S., 2017. Trusted autonomy between humans and robots: toward human-on-the-loop in robotics and autonomous systems. IEEE Syst. Man Cybern. Mag. 3 (1), 10–17.
Nguyen, N.H., Hadgraft, N.T., Moore, M.M., Rosenberg, D.E., Lynch, C., Reeves, M.M., Lynch, B.M., 2017. A qualitative evaluation of breast cancer survivors' acceptance of and preferences for consumer wearable technology activity trackers. Support. Care Cancer 25 (11), 3375–3384.
Nguyen, T.H., Vu, T.G., Tran, H.L., Wong, K.S., 2022. In: Emerging Privacy and Trust Issues for Autonomous Vehicle Systems, In 2022 International Conference on Information Networking (ICOIN). IEEE, pp. 52–57.
Owens, J.M., Antin, J.F., Doerzaph, Z., Willis, S., 2015. Cross-generational acceptance of and interest in advanced vehicle technologies: a nationwide survey. Transport. Res. Part F: Trac. Psychol. Behav. 35, 139–151.
Paddeu, D., Parkhurst, G., Shergold, I., 2020. Passenger comfort and trust on first-time use of a shared autonomous shuttle vehicle. Transport. Res. Part C: Emerg. Technol. 115, 102604.
Pellegrini, V., De Cristofaro, V., Salvati, M., Giacomantonio, M., Leone, L., 2021. Social exclusion and anti-immigration attitudes in Europe: the mediating role of Interpersonal Trust. Soc. Indic. Res., 1–28
Pettigrew, S., Talati, Z., Norman, R., 2018. The health benefits of autonomous vehicles: Public awareness and receptivity in Australia. Aust. N. Z. J. Public Health 42 (5), 480–483.
Porter, C.E., Donthu, N., 2006. Using the technology acceptance model to explain how attitudes determine internet usage: the role of perceived access barriers and demographics. J. Bus. Res. 59 (9), 999–1007.
Rahman, M.M., Deb, S., Strawderman, L., Burch, R., Smith, B., 2019. How the older population perceives self-driving vehicles. Transport. Res. Part F: Trac. Psychol. Behav. 65, 242–257.
Rahman, M.T., Dey, K., Das, S., Sherfinski, M., 2021. Sharing the road with autonomous vehicles: a qualitative analysis of the perceptions of pedestrians and bicyclists. Transport. Res. Part F: Trac. Psychol. Behav. 78, 433–445.
Rödel, C., Stadler, S., Meschtscherjakov, A., Tscheligi, M., 2014. Towards autonomous cars: the effect of autonomy levels on acceptance and user experience. In: Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, pp. 1–8.
Sener, I.N., Zmud, J., Williams, T., 2019. Measures of baseline intent to use automated vehicles: a case study of Texas cities. Transport. Res. Part F: Trac. Psychol. Behav. 62, 66–77.
Sousa, N., Almeida, A., Coutinho-Rodrigues, J., Natividade-Jesus, E., 2018. Dawn of autonomous vehicles: review and challenges ahead. Proceedings of the Institution of Civil Engineers-municipal Engineer vol. 171, 3–14.
Sparrow, R., Howard, M., 2017. When human beings are like drunk robots: driverless vehicles, ethics, and the future of transport. Transport. Res. Part C: Emerg. Technol. 80, 206–215.
Teetor, R.R., 1950. Speed control device for resisting operation of the accelerator. Google Patents.
Torgersen, H., Seifert, F., 1997. Aversion preceding rejection: Results of the eurobarometer survey 39.1 on biotechnology and genetic engineering in Austria. Public Underst. Sci. 6 (2), 131–142.
United Nations, Department of Economic and Social Affairs, Population Division, 2015. World Population Ageing 2015 (ST/ESA/SER.A/390).
Walker, W.E., Marchau, V.A., 2017. Dynamic adaptive policymaking for the sustainable city: the case of automated taxis. Int. J. Transp. Sci. Technol. 6 (1), 1–12.
Young, A.D., Monroe, A.E., 2019. Autonomous morals: Inferences of mind predict acceptance of AI behavior in sacrificial moral dilemmas. J. Exp. Soc. Psychol. 85, 103870.
Zavvos, E., Gerding, E.H., Yazdanpanah, V., Maple, C., Stein, S., 2021. Privacy and Trust in the Internet of Vehicles. IEEE Transactions on Intelligent Transportation Systems.
Zmud, J., Sener, I.N., Wagner, J., 2016. Self-driving vehicles: determinants of adoption and conditions of usage. Transp. Res. Rec. 2565 (1), 57–64.