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DOI
10.1016/j.trf.2019.05.008

Publication date
2019

Document Version
Final published version

Published in
Transportation Research Part F: Traffic Psychology and Behaviour

Transportation Research Part F 64 (2019) 184–195

Contents lists available at ScienceDirect

Transportation Research Part F

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

When will most cars be able to drive fully automatically? Projections of 18,970 survey respondents

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ARTICLE INFO

Article history:
Received 3 November 2018
Received in revised form 11 May 2019
Accepted 13 May 2019
Available online 22 May 2019

Keywords:
Crowdsourcing
Online surveys
Automated driving
Self-driving
Forecasting

ABSTRACT

When fully automated cars will be widespread is a question that has attracted considerable attention from futurists, car manufacturers, and academics. This paper aims to poll the public's expectations regarding the deployment of fully automated cars. In 15 crowdsourcing surveys conducted between June 2014 and January 2019, we obtained answers from 18,970 people in 128 countries regarding when they think that most cars will be able to drive fully automatically in their country of residence. The median reported year was 2030. The later the survey date, the smaller the percentage of respondents who reported that most cars would be able to drive fully automatically by 2020, with 15–22% of the respondents providing this estimate in the surveys conducted between 2014 and 2016 versus 3–5% in the 2018 surveys. Respondents who completed multiple surveys were more likely to revise their estimate upward (39.4%) than downward (35.3%). Correlational analyses showed that people from more affluent countries and people who have heard of the Google Driverless Car (Waymo) or the Tesla Autopilot reported a significantly earlier year. Finally, we made a comparison between the crowdsourced respondents and respondents from a technical university who answered the same question; the median year reported by the latter group was 2040. We conclude that over the course of 4.5 years the public has moderated its expectations regarding the penetration of fully automated cars but remains optimistic compared to what experts currently believe.

1. Introduction

Fully automated driving is expected to improve road safety and traffic flow efficiency and may have a considerable influence on transportation businesses (e.g., car insurance) and the shape of road infrastructure (Fagnant & Kockelman, 2015). Parking spaces within cities may soon no longer be needed, and road networks will likely change. Before fully automated driving becomes ubiquitous, appropriate transport policies will need to be developed regarding, for example, research funding, certification, liability, security, data privacy, communication protocols, vehicle registration, driving laws, taxes, insurance minimums, public-private cooperation, roadway design, and land use (for reviews and discussions on policies

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https://doi.org/10.1016/j.trf.2019.05.008
1369-8478/

regarding automated driving, see Anderson et al., 2016; Fagnant & Kockelman, 2015; Fraedrich, Heinrichs, Bahamonde-Birke, & Cyganski, 2019; Milakis, Van Arem, & Van Wee, 2017; Smith, 2017).

The direction of influence of transportation policies runs both ways. On the one hand, policies can affect the uptake of automated driving: progressive policies can accelerate uptake (Smith, 2017), whereas premature regulations "can run the risk of putting the brakes on the evolution toward increasingly better vehicle safety technologies" (NHTSA, 2013). In a scenario-construction study, 20 experts in the Netherlands predicted that between 7% and 61% of the vehicle fleet would be fully automated by 2050 (Milakis, Snelder, Van Arem, Van Wee, & Correia, 2017), depending on the restrictiveness versus progressiveness of the assumed transportation policies. On the other hand, transport policies are themselves influenced by technological developments and current levels of excitement about automated driving. Parkhurst and Lyons (2018) explained that policies for automated driving are constructed around a common understanding of an inherently uncertain future. These authors lamented the "enthusiasm shown by many policymakers" and that the economic promises regarding automated vehicles "have seduced some policymakers". Thus, it can be argued that responsible policymaking requires predicting when automated cars will be commonplace and regular monitoring of whether these predictions should be adjusted.

Futurists have long been concerned with making predictions about the introduction of automated vehicles. As early as 1940, Geddes outlined a blueprint of automated highway systems to be deployed in the United States (Geddes, 1940). In the late 1980s, Kurzweil predicted that by the end of the 1990s/early 2000s "the cybernetic chauffeur, installed in one's car, communicates with other cars and sensors on the roads. In this way it successfully drives and navigates from one point to another" (Kurzweil, 1990). In 2012, Kurzweil admitted that his prediction was wrong, yet noted that it was "not all wrong", considering the achievements in the Google self-driving car project (Kurzweil, 2012).

Predictions of the advent of fully automated driving have evolved from futurism to mainstream science and actual automotive practice. Automotive manufacturers are already testing their automated vehicles on public roads (Department of Motor Vehicles, 2018), with Waymo having reached the milestone of 10 million self-driven miles across 25 American cities (Waymo, 2018). However, these vehicles are not commercially viable yet and do not formally fulfil the definition of *fully* automated driving, because the automation occasionally disengages and a human driver has to take over control (Dixit, Chand, & Nair, 2016).

In August 2013, Nissan revealed plans for fully automated vehicles in 2020 (NissanNews.com, 2013), an estimate that was revised to 2022 in November 2017 (Nissan Motor Corporation, 2017) and repeated in March 2018 (Nissan Motor Corporation, 2018). In July 2016, BMW predicted that their first fully automated cars would be in production by 2021 (BMW News, 2016). In September 2018, the company presented the iNext model to be put in production in 2021; this is not an autonomous car but a highly automated one with a steering wheel that "retracts slightly" when in automated mode (BMW Group, 2018). Similarly, in August 2016, Ford announced that they expect their first fully automated cars for commercial ride sharing in 2021, although the chief technical officer of the company argued that fully automated cars with no steering wheel or pedals are unlikely to be available to customers before 2025 (Sage & Lienert, 2016). The company's website as of May 2019 still referred to 2021 as the year when "Ford will have a fully autonomous vehicle in operation by 2021 .... the vehicle will operate without a steering wheel, gas pedal or brake pedal within geo-fenced areas .... By doing this, the vehicle will be classified as a SAE Level 4 capable-vehicle" (Ford Motor Company, 2019). In June 2016, Continental stated that they would be ready for production of fully automated cars by 2025 (Continental AG, 2016), an estimate persisting in September 2018 (Continental AG, 2018a). On the one hand, automotive manufacturers are expected to make accurate predictions regarding the deployment of fully automated cars, because it is the car manufacturers that together with OEMs and ICT companies develop and will sell those vehicles. On the other hand, the predictions by automotive manufacturers presented in the media may not be the most reliable source of information, because of potential conflicts of interest in the market uptake.

Shladover, one of the pioneers of automated driving research in the United States, argued that it is unlikely for fully automated cars to arrive any time soon: "fully automated vehicles capable of driving in every situation will not be here until 2075. Could it happen sooner than that? Certainly. But not by much." (Shladover, 2016). In a survey among 217 attendees of an automated vehicle conference (31% of whom were employed in academia, 24% in the automotive industry, and 9% in government positions), Underwood (2014) observed a median of 2030 regarding the estimate when fully automated driving will be introduced to the market in the United States. Based on a survey among 3500 transport professionals in London, Begg (2014) reported that 10% of the respondents estimated that Level 4 vehicles would be commonplace on UK roads by 2030, whereas 20% reported 2040, 19% reported 2050, and 30% predicted that such a milestone would never be reached.

Besides polling the vision of automotive manufacturers, scientists, and other professionals, it is important to poll what the public thinks regarding the deployment of fully automated cars. It is the public who should eventually buy and use such vehicles and who will ultimately determine their future success. There is much to say about the hypothesis that aggregate predictions of a large number of individuals can be more reliable and accurate than the predictions of single experts, a phenomenon also known as the 'wisdom of crowds' or *vox populi* (Galton, 1907; Surowiecki, 2004). However, it has been found that only little social influence is required to undermine the wisdom-of-crowds effect (Lorenz, Rauhut, Schweitzer, & Helbing, 2011). The concept of automated driving has been said to be under the influence of media bias (Anania et al., 2018) and in the midst of a hype (Bartl & Rosenzweig, 2015; Lyons & Davidson, 2016). Shladover (2016) noted: "My concern is that the public's expectations have been raised to unreasonable levels because of the hype out there on the Internet". Drawing a parallel with the dot-com bubble between 1995 and 2001 (Ofek & Richardson, 2003), there may be significant risks associated with overconfident expectations regarding automated driving. If a hype indeed exists, the post-hype "trough of disillusionment" (cf. Fenn, 2007) may be characterized by a significant number of deprecated investments, preventable bankruptcies, and job losses. Hence, it ought to be monitored whether the crowd has overoptimistic expectations regarding the deployment of automated driving and whether these expectations are changing over time.

Previous surveys indicate that people appreciate automated driving, with a reduction in traffic accidents, emissions, and energy consumption being reported as important benefits (Bansal, Kockelman, & Singh, 2016; Piao et al., 2016; Schoettle & Sivak, 2014). Continental AG (2013, 2018b) polled the public's opinion on whether cars that drive themselves "will be a part of daily life in 5 to 10 years". Results showed optimistic responses, with between 37% and 75% of respondents in agreement with the statement, depending on the survey year, respondents' country, and the precise formulation of the question. Other survey research has revealed concerns about the security, privacy, legal liability, and ethical decisions of automated vehicles (Bonnefon, Shariff, & Rahwan, 2016; Kyriakidis, Happee, & De Winter, 2015; Schoettle & Sivak, 2014).

From the above, it is apparent that there is a lack of knowledge regarding when the public expects autonomous driving to be ubiquitous. This study aims to poll the public's expectation regarding the moment when fully automated cars will be widespread and whether this expectation has been adjusted over time. Accordingly, large numbers of respondents from more than 100 countries were polled over the last 4.5 years.

2. Methods

2.1. Surveys

Between June 2014 and January 2019, we performed 15 surveys via the crowdsourcing service CrowdFlower (nowadays called Figure-Eight), mostly to poll people's opinion on various aspects of automated driving, such as user's acceptance, worries, willingness to buy, and preferences for human-machine interfaces. In each survey, the following question was included: "*In which year do you think that most cars will be able to drive fully automatically in your country of residence?*" Here, we analyze the responses of the combined sample of respondents to this question across the 15 surveys. Table 1 shows the characteristics of the surveys. In all surveys, 'level 1' contributors (defined by the crowdsourcing platform as "All qualified contributors") was selected.

All data were collected anonymously. The surveys were approved by the Human Research Ethics Committee (HREC) of the Delft University of Technology. In all surveys, informed consent was obtained via a dedicated survey item asking whether the respondent had read and understood the survey instructions.

2.2. Data filtering

For each survey, we excluded respondents who did not indicate 'yes' to the question whether they had read the survey instructions, who indicated they were under 18 years old, who said they were older than 110 years, who did not respond to the question about their age or gender, or for whom no country information was provided by the crowdsourcing service. In some of the surveys, it was possible to generate multiple responses from different worker IDs with the same IP address. In these cases, we kept only the results from the first completion. The fastest 5% of the respondents were also removed from the analyses (as in De Winter & Dodou, 2016).

Responses reporting the year 2013 or earlier were excluded. If a respondent's answer equaled 'never' (i.e., single-word answer, case-insensitive), the answer was coded as 9999. Other textual responses were excluded from the analysis.

2.3. Analysis at the individual level

Analyses were conducted both at the individual level of respondents and at the national level. For the former, the distribution of the reported year (e.g., 25th percentile, median, 75th percentage) when most cars are expected to be able to drive fully automatically was provided (see Underwood, 2014). The reason for reporting percentiles rather than the mean or mode stems from the observation that the mean was severely affected by outliers (e.g., some participants reported a year thousands or even millions of years into the future), whereas the mode was regarded as insufficiently robust.

For respondents who participated in more than one of the 15 surveys, only the response from their first survey was included in this analysis. The reason for using the first survey was to ensure that trends in the reported year over time could be validly examined. If we had used responses from later surveys, then the results could have been affected by carryover effects from a prior survey.

Additionally, we calculated Spearman's rank-order correlations between the reported year and the following variables per respondent:

- the respondent's age;
- the respondent's gender;
- the respondent's self-reported violations. The self-reported violations were computed from Surveys 1, 3, 5, 6, 7, 9, 11, 13, 14, and 15, which included a 7-item Driver Behaviour Questionnaire (DBQ; De Winter, 2013). Specifically, we calculated:

Table 1
Overview of the 15 surveys.

Survey	Period of completion	Subject
S1 (De Winter et al., 2015)	Jun 16, 2014–Jun 17, 2014	Knowledge of automated driving systems and cross-national differences in traffic violations as measured with the Manchester Driver Behaviour Questionnaire (DBQ).
S2 (Kyriakidis et al., 2015)	Jul 4, 2014–Jul 7, 2014	User acceptance, worries, and willingness to buy partially, highly, and fully automated vehicles; cross-national differences and correlations with personal variables, such as age, gender, and personality traits as measured with a short version of the Big Five Inventory.
S3 (Bazilinskyy & De Winter, 2015)	Sep 2, 2014	User acceptance of auditory interfaces in modern cars and their willingness to be exposed to auditory feedback in highly and fully automated driving. A 7-item DBQ was also completed.
S4 (De Winter & Hancock, 2015)	Nov 29, 2014–Nov 30, 2014	Opinion on whether humans surpass machines or machines surpass humans.
S5 (Bazilinskyy, Petermeijer, Petrovych, Dodou, & De Winter, 2018)	Mar 31, 2015–Apr 1, 2015	Preferences for auditory, visual, and vibrotactile take-over requests in highly automated driving; the survey included recordings of auditory messages and illustrations of visual and vibrational messages. A 7-item DBQ was also completed.
S6 (De Winter & Dodou, 2016)	Dec 24, 2015–Dec 27, 2015	Relationships between traffic violations measured with a 7-item DBQ and traffic accident involvement.
S7 (Bazilinskyy & De Winter, 2017)	May 30, 2016–Jun 5, 2016	Effects of speech-based take-over requests on perceived urgency, commandingness, pleasantness, and ease of understanding; respondents listened to a random 10 out of 140 take-over requests and rated each take-over request in terms of the four aforementioned criteria. A 7-item DBQ was also completed.
S8 (Kovácsová, De Winter, & Hagenzieker, 2019)	Feb 27, 2017–Feb 28, 2017	Investigation of cyclists' behavior when approaching an intersection. The survey consisted of a questionnaire regarding cycling behavior, skills, and experience. Moreover, respondents watched videos from real traffic and answered questions about their predictions of what will happen next.
S9 (Bazilinskyy & De Winter, 2018)	Mar 3, 2017–Mar 4, 2017	Determination of reaction times for different types of visual and auditory signals. Respondents participated in a reaction-time measurement task and completed the DBQ.
S10 (Kovácsová et al., 2019)	Mar 4, 2017–Mar 7, 2017	Same as Survey 8, but now repeated among 15 selected Western high-income countries.
S11	Jun 16, 2017–Jun 18, 2017	Cross-national differences in traffic violations as measured with the DBQ.
S12 (Rodríguez Palmeiro, Van der Kint, Hagenzieker, Van Schagen, & De Winter, 2018)	Jul 7, 2017–Jul 12, 2017	Cyclist's behaviour when interacting with automated vehicles. Conducted among the same 15 selected Western high-income countries as S10.
S13	Apr 19, 2018–Apr 23, 2018	Cross-national differences in traffic violations as measured with the DBQ.
S14 (Bazilinskyy, Dodou, & De Winter, 2019)	Oct 3, 2018–Oct 29, 2018	External human-machine interfaces for automated driving.
S15 (Bazilinskyy, Dodou, & De Winter, 2019)	Dec 25, 2018–Jan 3, 2019	External human-machine interfaces for automated driving.

Note. In S2, only numeric entries were permitted, whereas in the rest of the surveys textual responses were also allowed. In S10 and S12, we only permitted respondents from 15 targeted Western high-income countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Sweden, Switzerland, United Kingdom, United States). In S2, a definition of full automation was provided: "Fully automated driving = The system takes over speed and steering control completely and permanently on all roads and in all situations. The driver sets a destination via a touchscreen. The driver cannot drive manually because the vehicle does not have a steering wheel". In S3, fully automated driving was explained as "Imagine a fully automated car (no steering wheel) that drives completely on its own with no manual interaction". In S5, highly automated driving was defined as "Highly automated driving = The automated driving car controls both speed and steering. The driver is not required to look at the road. If the automation cannot handle a situation, it provides a take-over request, and the driver must take over control", but no definition of fully automated driving was provided. In S12, people were divided into three groups and were given different definitions of automated driving (negative, neutral, positive). In S1, S4, S6–S11, and S13–S15, no definition of fully automated driving was provided.

  - a non-speeding violations score based on the following items: 1. using a mobile phone without a hands free kit, 2. driving so close to the car in front that it would be difficult to stop in an emergency, 3. sounding the horn to indicate annoyance with another road user, 4. becoming angered by a particular type of driver, and indicate hostility by whatever means one can, and 5. racing away from traffic lights with the intention of beating the driver next to own vehicle;
  - a speeding violations score from the following items: 1. disregarding the speed limit on a residential road, and 2. disregarding the speed limit on a motorway;
- the respondent's familiarity with automated driving. For this, we relied on Surveys 1, 6, 11, and 13, in which we asked respondents whether they had heard of the Google Driverless Car (also called Waymo), and Surveys 11 and 13, in which we asked whether respondents had heard of the Tesla Autopilot. The response options were 'Yes', 'No', and 'No response'.

A longitudinal analysis was also carried out to investigate whether respondents who participated in more than one of the surveys adjusted their expectations between their first and last survey.

2.4. Analysis at the national level

The analysis at the national level examined the relationships between the median years when most cars will be able to drive fully automatically and national developmental indexes. Specifically, we used the following variables per country:

- road traffic death rate per 100,000 population in 2013 (World Health Organization, 2015);
- gross domestic product (GDP) per capita in 2013 (World Bank, 2015);
- performance in educational tests (Rindermann, 2007);
- average life expectancy in 2013 (World Bank, 2015);
- self-reported speeding violations and non-speeding violations (from Surveys 1, 3, 5, 6, 7, 9, 11, 13, 14, 15);
- motor vehicle density (cars, buses, and freight vehicles, but not two-wheelers, per 1,000 people) averaged over the years 2003–2010 (World Bank, 2015);
- median age in 2014 (Agency, 2015).

In the national analysis, to reduce sampling error, we selected only those countries with 25 or more respondents having provided a numeric response or 'never'. If a respondent had completed more than one of the 15 surveys, the responses were averaged across the completed surveys. The reason for averaging of responses was that the goal of the analysis at the national level was to examine differences between countries, rather than to investigate trends over time. Thus, we relied on the principle of aggregation to obtain a statistically reliable estimate of the reported year (Rushton, Brainerd, & Pressley, 1983).

We calculated a Spearman correlation matrix of the median year of introduction of fully automated cars as collected from the surveys, respondents' gender (percentage of male respondents in each country), respondents' mean age, and the aforementioned national variables.

3. Results

3.1. Results at the individual level

Table 2 provides descriptive statistics of the respondents per study. There were 21,017 respondents from 130 countries, of whom 18,970 respondents in 128 countries provided a numeric response to the question of interest or answered 'never'. These 18,970 responses exhibited a skewed distribution, with a clear zero end-digit preference (Fig. 1).

Table 3 shows that across the 15 surveys, 23–49% of the respondents reported a year between 2017 and 2029. The median predicted year across all surveys was 2030. Respondents in the more recent surveys were less likely to report that most cars will drive fully automatically by 2020 (Fig. 2), with 15–22% of the respondents providing this estimate in the surveys conducted between 2014 and 2016 versus 3–5% in the 2018 surveys (Table 3).

Table 2
Respondents' characteristics.

Survey	Survey date	# respondents	# respondents included	# unique countries	# respondents reporting a numeric year	# respondents reporting 'never'	% males	Mean (*SD*) age
S1	Jul 2014	1854	1711	91	1520	44	66.8	32.7 (11.3)
S2	Jul 2014	5000	4365	105	3709	0	68.9	32.8 (10.9)
S3	Sep 2014	2000	1656	95	1481	13	74.6	31.6 (10.5)
S4	Nov 2014	2999	2800	103	2625	22	71.9	31.8 (11.0)
S5	Mar 2015	3000	2794	101	2581	9	73.5	32.4 (10.3)
S6	Dec 2015	3250	2935	95	2654	34	69.8	33.8 (10.6)
S7	May 2016	3061	2842	98	2616	20	66.7	33.8 (10.6)
S8	Feb 2017	700	633	60	550	5	75.1	32.6 (9.4)
S9	Mar 2017	2000	1848	84	1702	14	70.6	34.0 (10.1)
S10	Mar 2017	700	638	15	593	10	48.8	38.0 (11.7)
S11	Jun 2017	2500	2249	92	2069	22	69.0	33.1 (10.7)
S12	Jul 2017	700	630	15	597	4	47.1	38.6 (12.6)
S13	Apr 2018	3000	2627	84	2427	22	64.4	33.7 (10.8)
S14	Oct 2018	1770	1586	73	1441	7	63.3	34.6 (11.3)
S15	Dec 2018	2001	1802	77	1665	8	65.6	36.0 (11.5)
	Total		21,017	130	18,810	160	69.2	31.7 (10.2)

Note. The percentage of male respondents and the respondents' mean age were calculated for the respondents who reported a numeric year or 'never'.

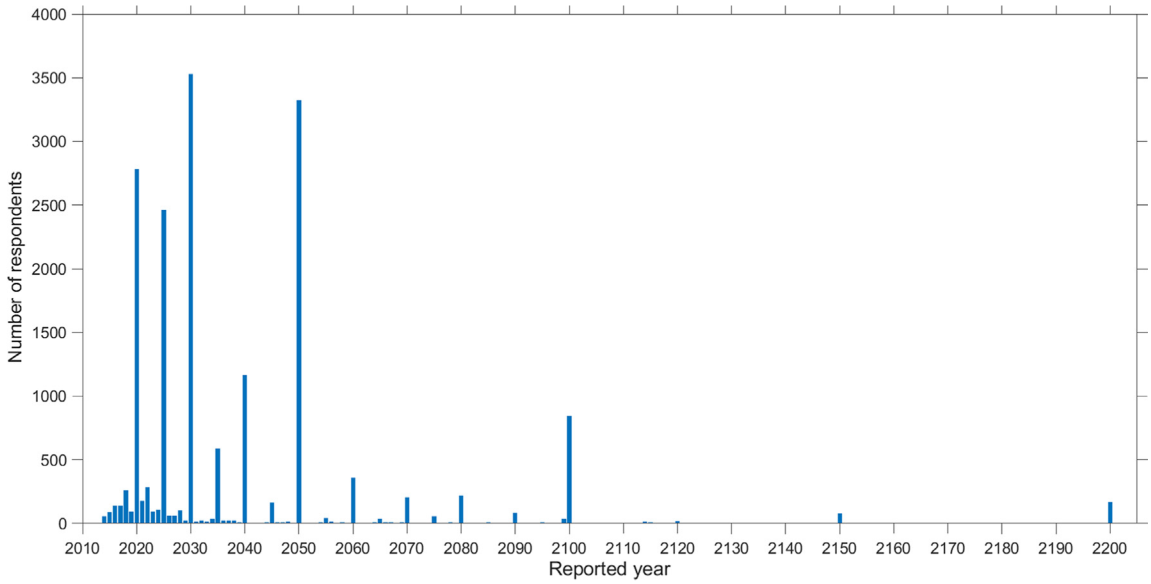

Fig. 1. Distribution of the reported year for all surveys combined (N = 18,970, of which 18,314 reported a year in the range 2014–2200).

Table 3
Distribution of the reported year per survey.

Survey	Survey date	Median year (P25, P75)	Percentage of respondents			
			2020	2030	2017–2029	2075+ (including 'never')
S1	Jul 2014	2030 (2022, 2050)	18	16	34	16
S2	Jul 2014	2030 (2021, 2050)	19	17	38	11
S3	Sep 2014	2030 (2020, 2050)	22	16	42	11
S4	Nov 2014	2030 (2025, 2050)	16	16	35	14
S5	Mar 2015	2030 (2020, 2045)	22	19	47	7
S6	Dec 2015	2030 (2025, 2050)	16	17	37	12
S7	May 2016	2030 (2025, 2050)	15	20	38	10
S8	Feb 2017	2035 (2025, 2050)	9	18	30	17
S9	Mar 2017	2030.5 (2025, 2050)	10	19	30	13
S10	Mar 2017	2030 (2025, 2040)	14	21	43	9
S11	Jun 2017	2030 (2025, 2050)	9	22	30	12
S12	Jul 2017	2030 (2025, 2035)	13	21	49	4
S13	Apr 2018	2035 (2030, 2050)	5	22	24	14
S14	Oct 2018	2035 (2030, 2050)	4	24	23	14
S15	Dec 2019	2030 (2030, 2050)	3	26	24	11
	Total	2030 (2025, 2050)	15	19	35	12

Fig. 3 shows correlations between individual characteristics and the reported year when most cars will drive fully automatically. Males reported a significantly higher year than females ($p = 0.002$), although the effect was minimal ($\rho = 0.02$). There were no significant correlations of the reported year with age, nor with self-reported traffic violations. However, people who were more familiar with automated driving technology (i.e., who had heard of the Google Driverless Car (Waymo) or the Tesla Autopilot) provided a more optimistic response than participants who answered 'no' to these questions ($p < 0.001$). The percentage of respondents who had heard of the Google Driverless Car was 48%, 57%, 56%, and 45%, for Surveys 1, 6, 11, and 13, respectively), and the percentage of respondents who answered 'yes' to the question of whether they had heard of the Tesla Autopilot was 55% and 60% for Surveys 11 and 13, respectively.

5,803 respondents completed 2 or more of the 15 surveys, and 5,237 of them reported a year in at least two surveys. Among these 5,237 respondents, 25.3% indicated the same year in their first and last survey, 39.4% revisited their estimate upward, and 35.3% revisited their estimate downward. The year reported in the returning respondents' first and last surveys was significantly different (Wilcoxon signed-rank test: $p < 0.001$, sign statistic = 1851, z value = -3.34, Spearman ρ between the respondents' first and last survey = 0.49).

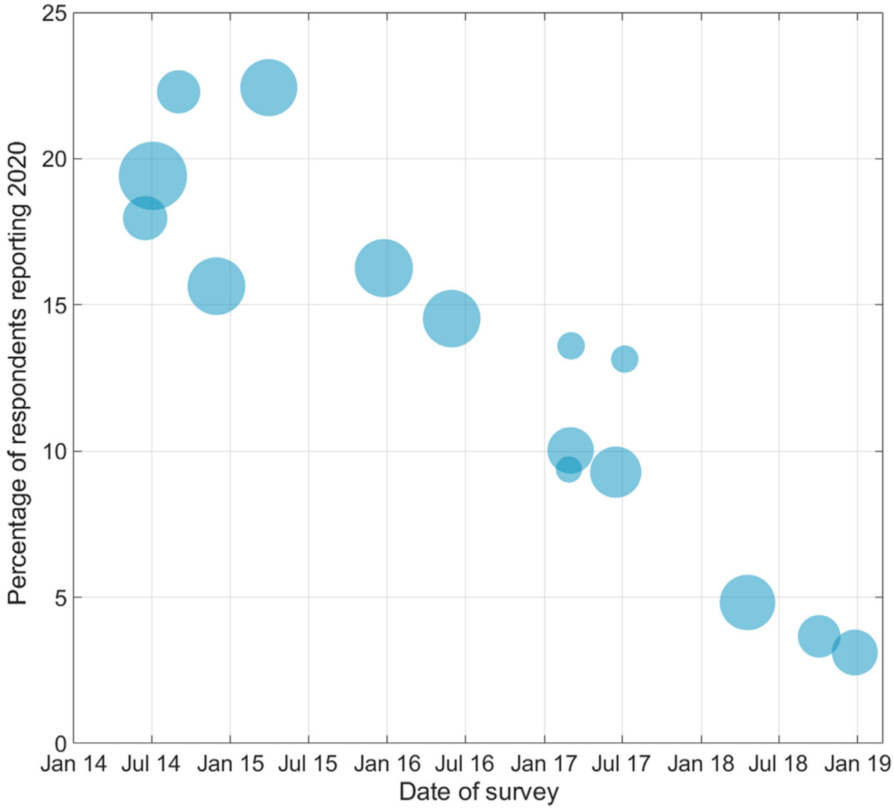

Fig. 2. Percentage of respondents reporting '2020', as a function of the survey start date. The area of each circle linearly corresponds to the number of respondents who provided a numeric response or reported 'never'.

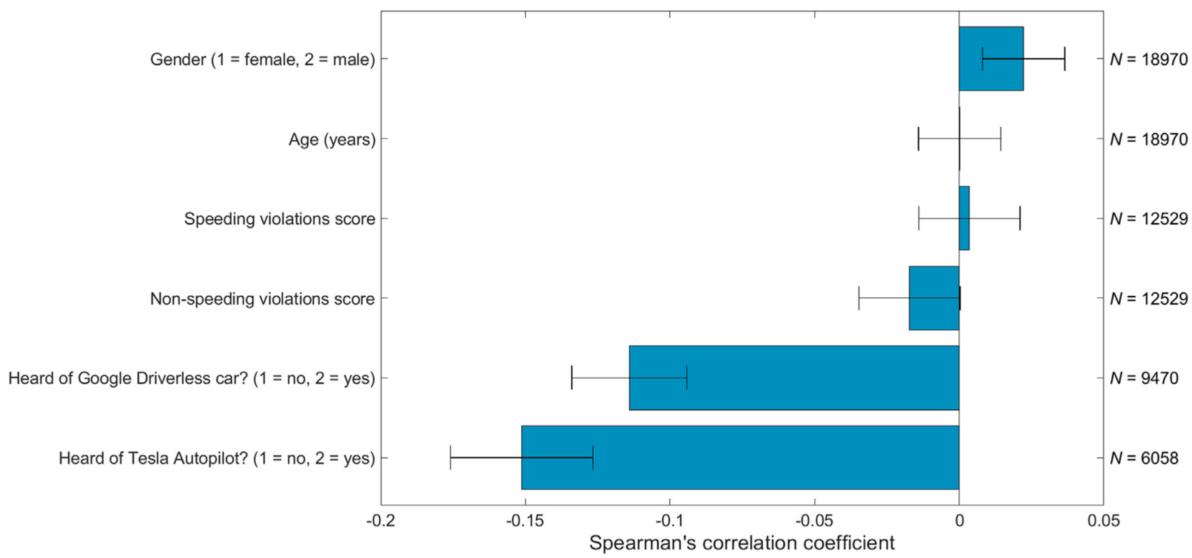

Fig. 3. Spearman's correlation coefficients (equivalent to Pearson correlations after rank-transforming the variables) between the reported year and various individual characteristics. The error bars represent 95% confidence intervals.

3.2. Results at the national level

Table 4 shows cross-national correlations for the 65 countries with 25 or more respondents. There was a tendency of people in more highly developed countries (in terms of variables 6–11) to report an earlier median year ($|\rho| < 0.34$). For example,

Table 4
Spearman correlation matrix between the median reported year, percentage males, mean age, and mean violations scores per country, together with various national statistics ($N = 65$; $N = 58$ for the mean speeding and non-speeding violations).

	1	2	3	4	5	6	7	8	9	10
1 R: median year										
2 R: gender (% males)	0.24									
3 R: mean age	−0.15	−0.65								
4 R: self-reported speeding violations score	0.22	−0.06	0.13							
5 R: self-reported non-speeding violations score	0.19	0.56	−0.56	0.19						
6 S: road traffic death rate per population	0.19	0.44	−0.54	−0.05	0.73					
7 S: GDP per capita (US$)	−0.34	−0.49	0.62	0.07	−0.67	−0.73				
8 S: educational performance	−0.11	−0.55	0.61	0.15	−0.73	−0.80	0.78			
9 S: life expectancy	−0.24	−0.42	0.48	0.11	−0.63	−0.79	0.87	0.79		
10 S: motor vehicle density per population	−0.18	−0.60	0.73	0.26	−0.63	−0.67	0.84	0.77	0.76	
11 S: median age	0.10	−0.50	0.59	0.30	−0.60	−0.71	0.64	0.77	0.67	0.76

Note. 'R' indicates that data that were obtained from the respondents. 'S' indicates that data that were obtained from previously published national statistics.

the percentage of respondents indicating '2020' across all surveys was 20.0% in the United States (GDP per capita: $52,980), 17.9% in India (GDP per capita: $1455.1), and 8.2% in Venezuela (GDP per capita: $12,265; see also Fig. S1). However, the correlations between the reported median year and the national variables were small compared to the correlations between the national variables themselves (i.e., variables 6–11 exhibit correlations of $|\rho| > 0.63$). Fig. 4 illustrates that the country's GDP per capita was moderately correlated with the median year, with the higher-income countries (GDP per capita >20,000 US$) featuring a median year below 2040, and typically around 2030 or even 2025. Fig. 5 shows that GDP per capita strongly correlated with self-reported non-speeding violations. Table S1 in the supplementary material presents results for each country separately.

The country representation in the surveys changed over time. For example, while the percentage of respondents who were from the United States and India showed a decrease (US: 8% in S1, 5% in S15; India: 10% in S1, 6% in 2015), the percentage of respondents who were from Venezuela increased substantially (2% in S1, 41% in S15). This change in demographic composi-

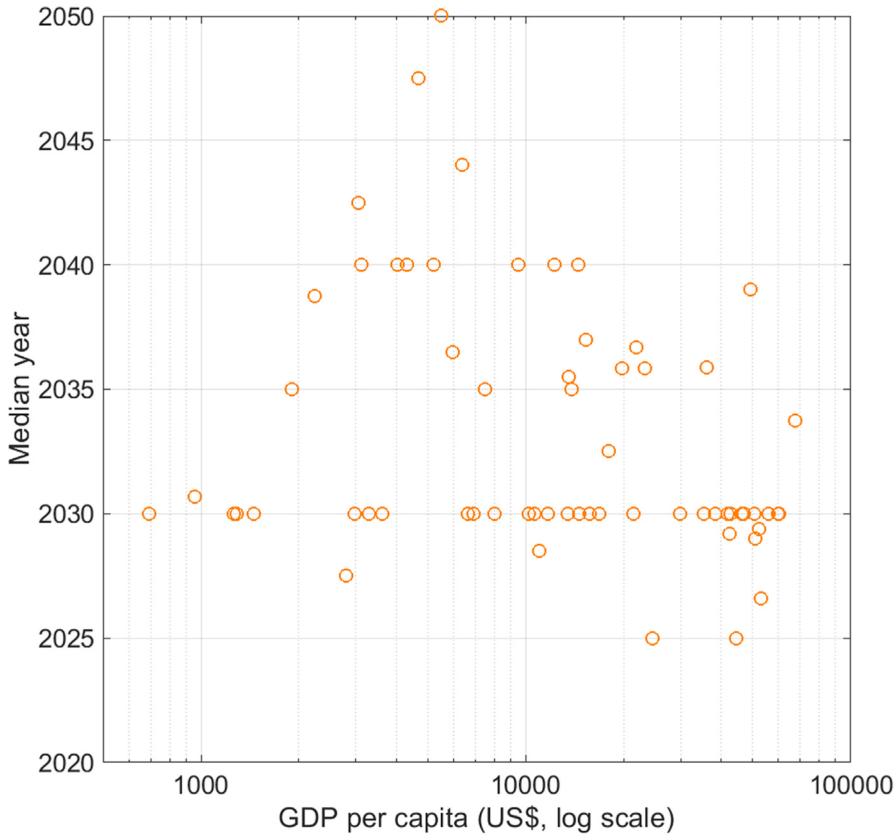

Fig. 4. Median predicted year versus gross domestic product (GDP) per capita ($\rho = -0.34$). Each marker represents a country.

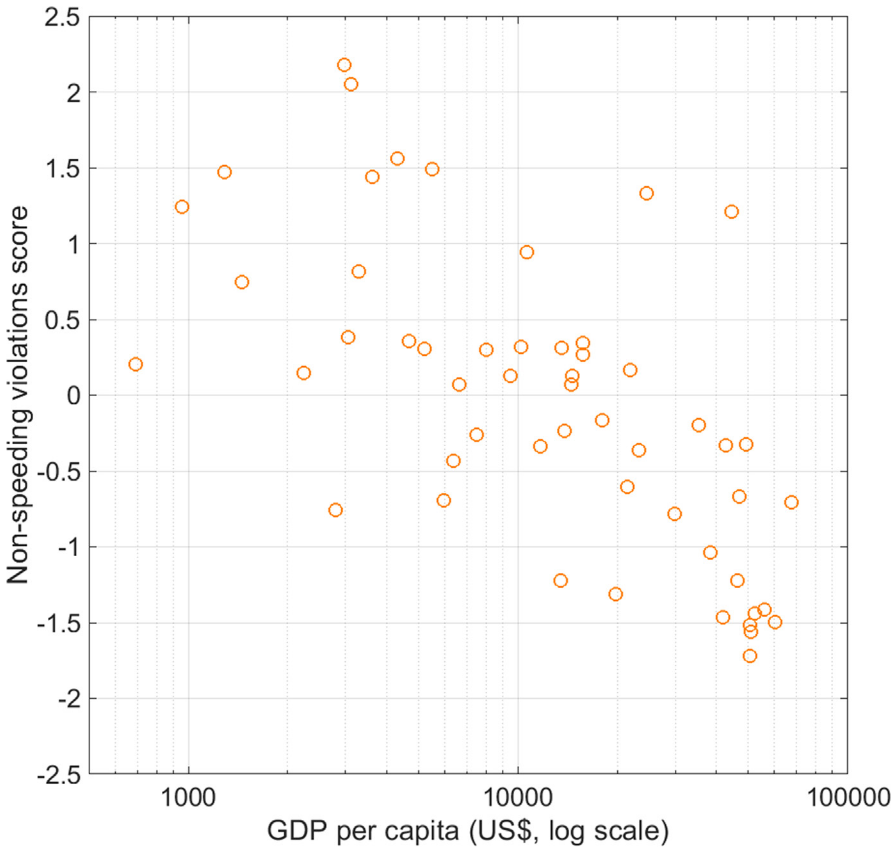

Fig. 5. Non-speeding violations score versus gross domestic product (GDP) per capita ($\rho = -0.67$). Each marker represents a country.

tion could represent a confounder for the temporal trend of the overall percentage of respondents who reported '2020' (Fig. 2). However, subgroup analyses indicated that the percentage of respondents who reported 2020 dropped for each of these countries, indicating that the recalibration of participants' expectations is robust across countries, and not an artefact.

3.3. Control study with participants from a technical university

In addition to the crowdsourced surveys, we conducted a control study of S7 in March 2017. This control study was performed with 38 participants (31 males, 7 females, mean age = 26.6 years, *SD* age = 6.5 years). The participants were students and staff members of the Faculty of Mechanical, Maritime and Materials Engineering at the Delft University of Technology.

The control sample reported a median year of 2040 (P25 = 2027, P75 = 2050). The minimum reported year was 2022. In comparison, across the 15 online surveys, there were 121 respondents from the Netherlands, of which 113 reported a year or 'never'; their median reported year was 2028.

4. Discussion

Over the course of 4.5 years, we conducted 15 online surveys in which we asked respondents when most cars will be able to drive fully automatically in their country of residence. The first survey in which we asked this question was June 2014 (De Winter, Kyriakidis, Dodou, & Happee, 2015) and the last survey ran until January 2019.

The median reported year across all 15 surveys was 2030, which is more optimistic than previously published expert estimates (Begg, 2014; Litman, 2018; Milakis, Snelder, et al., 2017; Shladover, 2016; Underwood, 2014). Underwood (2014) reported 2030 as median estimate of when fully automated driving will be *introduced* to the market (where fully automated vehicles were defined as "Vehicle is in control from beginning to end of trip, both on highway and surface streets, urban and rural, without human intervention"), whereas in our surveys, we polled the respondents' opinion about the year when *most cars* will be able to drive fully automatically in their country of residence.

Returning respondents on average revised their initial estimate to a later year. In our first surveys launched in 2014–2016, between 15 and 22% of respondents reported 2020 as the predicted year, and this had reduced to 3–5% in the surveys deployed in 2018. This recalibration of predictions can be explained by the fact that in 2014–2016, 2020 still appeared to be 'far away', making it plausible that most cars could drive fully automatically by then. In the last survey, 2020 was only one year away, making it evident that fully automated cars will not be ubiquitous by then. Our observations are in line with a recent statement by the CEO of Ford Motor Company: "We overestimated the arrival of autonomous vehicles" (Detroit Public, 2019, 43:23).

There are several reasons why 2030 can be regarded as a too optimistic prediction of when most cars will be able to drive fully automatically. First, there may be a large temporal lag between the introduction of fully automated vehicles and their widespread adoption. For Electronic Stability Control (ESC), for example, the lag was 20 years: ESC was introduced in 1995 and is included in most registered vehicles in the US since 2015 (Zuby, 2016). Kröger, Kuhnimhof, and Trommer (2019) estimated penetration rates of fully automated vehicles by 2035 between 10% and 38% in Germany and between 8% and 29% in the United States. By taking into account the turnover rate of modern cars, Litman (2018) forecasted that 40% of the vehicle fleet would consist of fully automated vehicles by 2040. The introduction of fully automated cars may be accompanied by a shift in the organization of road transport. Examples are dedicated lanes for automated driving, and vehicle sharing via dynamic trip-vehicle assignment (Alonso-Mora, Samaranayake, Wallar, Frazzoli, & Rus, 2017). Such innovations, together with governmental mandates, accelerating technological change, and growing public acceptance, may make it possible that the lag between the introduction of fully automated cars and their widespread use will be shorter than the aforementioned 20 years. Second, the computer intelligence required for fully automated driving is high (Geiger, Lauer, Wojek, Stiller, & Urtasun, 2014; Ohn-Bar & Trivedi, 2016). Sierhuis pointed out that fully automated cars will need to anticipate whether a pedestrian will cross the road based on the body language of that pedestrian: "Can you imagine our autonomous vehicles figuring out that they [pedestrians] are not going to cross? That is a very very complex problem to solve." (Sierhuis, 2016, 49:38; see also Vinkhuyzen & Cefkin, 2016).

Crowdsourcing respondents may not be representative of the general population. It has been argued that individuals who complete research tasks via crowdsourcing services are a relatively limited (<10,000) poll of people who have developed into specialized research participants (Chandler, Mueller, & Paolacci, 2014; Stewart et al., 2015). Another limitation is that the topic of each survey differed, which may have affected the way the respondents' interpreted the question under investigation. Moreover, our study was partly longitudinal, as 'only' 5,803 respondents completed two or more surveys. The participant pool varied over the years, and some countries were more represented in some surveys than in others. For example, S10 and S12 were conducted among 15 selected European countries, and these two surveys appear as outliers, with a relatively large amount of respondents '2020'. Regardless of these limitations, the results appear robust, with the median reported year around 2030, and a recalibration of expectations regarding the year '2020', also at the country level (see Fig. S1).

It is possible that respondents gave a fast and intuitive answer and did not deliberatively reflect on the future of automated driving. The fact that respondents gave more optimistic predictions than experts may be because the notion of fully automated driving was unclear to the respondents. Some respondents may have been thinking about technology that is formally known as highly, conditionally, or partially automated driving systems (such as the Tesla Autopilot). Future research could be conducted using multiple-item surveys and explicit definitions or multimedia illustrations of fully automated driving. User acceptance of, worries about, and willingness to buy partially, highly, and fully automated vehicles (cf. Continental AG, 2013, 2018b; Kyriakidis et al., 2015) would also deserve to be longitudinally monitored.

Our results show that respondents who indicated that they had heard of the Google Driverless Car (Waymo) or the Tesla Autopilot provided more optimistic estimates regarding when most cars will be able to drive fully automatically in their country of residence. In line with this finding, respondents from higher-income countries reported an earlier median year. An explanation is that high-income countries have high-quality road infrastructure on which automated vehicles can be deployed. A second explanation is that most companies developing fully automated vehicles are located in high-income countries. Third, in high-income countries, more people are able to afford luxury goods, such as automated cars. It may also be that these answers have been confounded, as respondents from higher-income countries were more likely to be female and older (Table 4), and exhibit a more law-abiding driving style than respondents in lower-income countries (Fig. 5). More specifically, there is a risk of an ecological fallacy, as correlations at the national level are not necessarily generalizable to the individual level (Pollet, Tybur, Frankenhuis, & Rickard, 2014). To illustrate, in Survey 2, we asked respondents about their yearly income via a multiple-choice item. For each country with 25 or more respondents, we calculated the Spearman rank-order correlation between the participants' reported year and their income. The median correlation of the 37 countries was −0.01. In other words, the correlation between the predicted year and income is observed between countries ($\rho = -0.34$, see Table 4), not within countries ($\rho = -0.01$).

As mentioned in the Introduction, it is important to poll the public's opinion regarding the future of automated driving. Automated driving is a promising development, but policymakers should not be seduced to ride a hype that may exist among the public. With the caveats noted above, we observed that the crowdsourced public gave more optimistic predictions about the ubiquity of fully automated driving than experts. Additionally, over the course of 4.5 years, the crowd has toned down its projections regarding the deployment of fully automated cars, both longitudinally and cross-sectionally. We hope that this paper stimulates a discussion on the hype cycle of automated driving.

Acknowledgments

The research presented in this paper is being conducted in the project HFAuto – Human Factors of Automated Driving (PITN-GA-2013-605817).

Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2019.05.008, Furthermore, raw data and scripts are available at https://doi.org/10.4121/uuid:ed63e704-ac75-4f96-a2d7-4c8e3b48b168.

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