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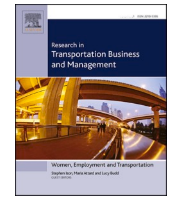

The expected speed and impacts of vehicle automation in passenger and freight transport: A Dissensus Delphi study among UK professionals

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ABSTRACT

Vehicle automation is one of the most researched topics in transport studies but much remains uncertain about the speed of adoption and potential impacts, including if and how it can contribute to greater environmental sustainability. This study adopts a Delphi approach to examine the speed with which 15% of new vehicles will be automated (SAE-3, SAE-4 or SAE-5) and what impacts automation may have on motility, mobility, resource use and externalities in both passenger and freight transport. Although challenges with recruitment mean that all findings must be caveated and seen as exploratory, the analysis demonstrates considerable dissensus regarding the expected speed and impacts of vehicle automation in both passenger and freight transport among the participants. For both aspects, a diversity of views remains once participants were informed about the expectations of other panellists. The range of views is organised around the axes of optimism and certainty about what may happen. Considerable differences between passenger and freight transport can be identified for potential impacts of vehicle automation but not for speed of adoption.

1. Introduction

Automated vehicles (AVs) are at the forefront of many imaginings of transport futures. There is, however, much uncertainty over the likelihood of emergence and widespread diffusion, time frames, impacts and implications. Claims of potential benefits commonly include increased safety and accessibility, and decreased congestion, monetary costs, emissions and energy demand (HM Government, 2022; Shiwakoti, Stasinopoulos, & Fedele, 2020). It remains unclear, however, to what extent these will be realised and how their realisation depends on the level of automation and the configuration of wider transport and land use system (e.g., Buldeo Rai, Touami, & Lablanc, 2022; Harb, Stathopoulos, Shiftan, & Walker, 2021; Nikitas, Thomopoulos, & Milakis, 2021). Moreover, the very idea of AVs remains contentious (Lyons, 2022), and the possibility of significant downsides of vehicle automation cannot be dismissed. Examples of the latter include major rebound effects in the form of increased vehicle mileage, increased inequity, diminished physical activity, intensified urban sprawl, and deterioration of public finances (e.g., Wadud et al., 2016; Booth, Norman, & Pettigrew, 2019; Milakis & Müller, 2021; Blas, Giacobone, Massin, & Rodríguez Tourón, 2022).

Recent years have witnessed numerous surveys on AV perceptions and attitudes (e.g., Gkartzonikas & Gkritza, 2019; Harb et al., 2021). Such surveys tend to gauge the population of interest's awareness, expectations and/or acceptance of AV technologies. Most have focused on the general public; far fewer have considered the views of those who are more closely connected to AV development – that is, the 'professionals' or 'experts' across the diverse domains which contribute to this innovation (Liu, Nikitas, & Parkinson, 2020; Rezaei & Caulfield, 2021). At the same time, and reflecting broader trends within transport scholarship, there is a primary focus on passenger transport (but see Buldeo Rai et al., 2022), even if much industry effort is devoted to vehicle automation as a means to reduce costs in freight transport (Wadud, 2017).

This paper presents research adopting the Delphi method, an approach traditionally used to develop consensus among a group of people on a topic where there is a diversity of perspectives. In this paper, however, we use an alternative version of the method, focused on disagreement and nurturing the diversity of perspectives. Several studies have demonstrated the usefulness of allowing for dissensus in Delphi studies of possible futures for passenger and freight transport (Julsrud & Uteng, 2015; Tapio, 2003), and this design seems particularly germane in the context of vehicle automation. Given AVs' polarising nature

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(Nielsen & Haustein, 2018), there is growing recognition of the need to move beyond consensus building in research on expectations about vehicle automation and to identify co-existing discourses and factions and how these relate to each other (Lyons, 2022). Using a dissensus Delphi design, we address the question: *What are the expectations of a diverse panel of 'professionals' working on aspects of vehicle automation relating to the timelines for diffusion and potential impacts of automation for freight and passenger transport*? The novelty of this paper lies at the intersection of 1) its focus on both passenger and freight transport, 2) the application of a dissensus Delphi, and 3) its focus on 'professional' rather than 'public' perceptions.

2. Literature review

There is an ever-growing literature examining multiple, interdependent dimensions of vehicle automation, and even the number of review papers is rapidly increasing. Much scholarship questions *if* vehicle automation will happen; *when* particular versions of vehicle automation will mainstream and *where* vehicle automation might occur first; *whether* vehicle automation will be accepted by parts, or all, of the population; and *what consequences* vehicle automation might have for transport systems and their externalities. As future-oriented exercises, studies addressing these dimensions are largely speculative. They often report the articulated expectations of people who have yet to have any direct experience of a fully autonomous vehicle (although they may have driven a partially automated one – Hardman, 2021), and are affected by the language used to describe this innovation (i.e., self-driving, driverless, fully automated, autonomous – Kassens-Noor, Wilson, Cai, Durst, & Decaminada, 2021).

The *if* and *when* questions of AV adoption are of interest to the private sector as well as transport planners and engineers (Asmussen, Mondal, & Bhat, 2020). Many factors shape the speed of automated vehicle adoption across passenger and freight. For passenger vehicles, vehicle lifespan and fleet turnover rates (Held, Rosat, Georges, Pengg, & Boulouchos, 2021) limit the speed with which new innovations can accelerate market share, with due implications for lifecycle emissions (Naumov, Keith, & Sterman, 2022). Fleet turnover is usually faster in freight transport due to tightening emissions standards although small freight companies, including owner-operator hauliers, often struggle to adapt to changing regulation as easily as larger firms (Meelen, Doody, & Schwanen, 2021).

Studies vary in their estimations and results for AV uptake. According to a recent study by Weigl, Eisele, and Riener's (2022) in Germany, SAE level-3 (SAE-3) vehicles will be accepted and adopted in about 10 years, while SAE-5 will be accepted and adopted in 20 years. A study comparing surveys among 18,970 people in 128 countries in 2014–2019 has suggested that, over time, people have "moderated [their] expectations regarding the penetration of fully automated cars but remain optimistic compared to what experts currently believe" (Bazilinskyy, Kyriakidis, Dodou, & de Winter, 2019, page 184). Little is known about expected uptake in freight transport, though Buldeo Rai et al. (2022, page 10) report that interviewed "transport companies [in France] believe that autonomous vehicles will deliver up to a quarter of the e-commerce volume within ten years".

As explained above, multiple potential impacts of automated vehicle adoption – both positive and negative – have been posited. We propose to categorise potential impacts into four classes (Table 1): 1) *motility*, or the potential or capacity for mobility (Kaufmann, 2002); 2) *mobility*, or realised trips and movements; 3) *resource use*, or the financial means and energy used for mobility; and 4) *externalities* generated by mobility.

The literature on the motility implications of AVs concentrates on accessibility and vehicle ownership. AVs are widely claimed to enhance the *accessibility* of private vehicle transport for those currently excluded from it for age, health, affordability and other reasons (Jeon et al., 2016). The realisation of accessibility increases will depend on multiple factors, including the willingness of non-drivers to use automated vehicles, assumptions about automated vehicles (e.g., level of automation, market penetration, ownership model), and wider societal and regulatory dynamics (Dianin, Ravazzoli, & Hauger, 2021; Kottasz, Bennett, Vijaygopal, & Gardasz, 2021). Key will be whether policy will steer AV deployment towards making compact urbanisation and multimodal transport more attractive, or rather reinforce urban and/or private vehicle ownership. Dianin et al. (2021) propose four possible 'accessibility impacts': physical accessibility polarisation (contributing to compact urbanisation and multi-modality); physical accessibility sprawl; exacerbation of social accessibility inequities; and alleviation of social accessibility inequities.

Table 1
Themes from literature guiding empirical analysis. Note: the right hand column notes the primary relevance of these dimensions for passenger and/or freight transport, however, all dimensions were used for the analysis presented.

Theme name	Theme description	Potential impacts	Passenger (p) or Freight (f)
Motility	The potential to become mobile using a SAE-level 3–5 vehicle	(1) increased accessibility (2) increased (private) vehicle ownership	(p) (p)
Mobility	Actual movements through physical space using a SAE-level 3–5 vehicle	(1) increased vehicle miles (2) decreased use of other modes	(p) and (f) (p) and (f)
Resource implications	Resource implications of SAE-level 3–5 vehicle usage	(1) reduced costs (2) decreased energy demand (3) increased energy use	(p) and (f) (p) and (f) (p) and (f)
Externalities	Externalities of SAE-level 3–5 vehicle usage	(1) increased road safety (2) decreased air pollution (3) reduced carbon emissions (4) increased traffic congestion (5) increased urban sprawl (6) decreased physical activity	(p) and (f) (p) and (f) (p) and (f) (p) and (f) (p) (p) and (f)

AV *ownership models* constitute an important dimension of vehicle automation's capacity to reduce inequities in transport (Dianin et al., 2021; Wadud & Mattioli, 2021), with a recent micro-simulation model showing on-demand usage models for AVs to increase accessibility (Zhou, Le, Nguyen-Phuoc, Zegras, & Ferreira, 2021). However, according to a recent review of past research (Harb et al., 2021), most people prefer owning AVs to sharing them, with pooled sharing the least popular option. Similarly, Lee, Lee, Park, Lee, and Ha (2019) argue that psychological ownership – a *feeling* of ownership – could be important for potential AV users. Research on AV accessibility and ownership has focused on passenger transport; we are not aware of studies of these dimensions in relation to freight transport.

The debate on mobility and AVs tends to revolve around impacts on *modal split* and *vehicle mileage*, with due implications for resource use in the form of *financial costs* and *energy consumption*. Both public surveys and review studies conclude that widespread AV adoption in passenger transport will probably reduce public transport use (Booth et al., 2019; Harb et al., 2021; Lehtonen et al., 2021; Spence et al., 2020). The review by Harb et al.'s (2021) suggests the decline may fall in the range of 9–70%. The impacts on active transport may be more equivalent, with Booth et al. (2019) suggesting that the ultimately prevailing ownership model for AVs will decide whether cycling and walking will grow or decline. A qualitative study among 15 transport experts from academia and the public and private sectors in the USA suggests that widespread AV adoption may increase cycling and walking because of greater road safety and more road space becoming available for active transport (Botello, Buehler, Hankey, Mondschein, & Jiang, 2019). However, safety concerns during the transition towards autonomous driving, increased regulation of cycling and walking to make sharing the road with AVs easier, and the increased attractiveness of cars might all diminish cycling and walking (ibid.).

Looming large is the risk of direct rebound effects, with vehicle miles travelled (VMT) increasing because of the lower cost of operating AVs. Applying microeconomic modelling to 2017 US national household travel survey, Taiebat, Stolper, and Xu (2019) forecast vehicle mileage to increase by 2–47% and especially among high-income households. This growth may even translate in a net rise in energy use. Rebound effects will be intensified by AVs' ability to generate 'zombie miles', or empty kilometres. Zhang, Guhathakrta, and Khalil (2018) show that use of privately owned AVs could reduce vehicle ownership levels for 18% of households in the Atlanta Metropolitan Area while maintaining their current travel patterns; however, the zombie miles associated with private AV use can increase total VMT in the region by at least 13%. The extent of zombie mileage will depend on the AV ownership and service model and probably be highest for on-demand exclusive use services (Wadud & Mattioli, 2021). Harb et al. (2021, page 30) confirm that most studies predict increasing VMT although this "varies considerably across the literature and ranges from a low of 1% to a high of 90% depending on the scenario—shared vs. privately owned—and the assumptions made on changes in travel behaviour".

For freight transport, the evidence about direct rebound effects is less clear and mostly focused on platooning – an innovation for which profound uncertainty over the scale of adoption exists (Paddeu & Denby, 2022). Vahidi and Sciarretta's (2018) review indicates that platooning for trucks could generate energy savings of 7–10% from drag reduction, whereas Wadud, MacKenzie, and Leiby (2016) suggest that platooning could reduce energy use but that this effect can be superseded by direct rebound effects at higher levels of automation. Sun, Wu, Abdolmaleki, Yin, and Zou (2021), meanwhile, suggest that the energy savings due to platooning will depend on the allowable platoon size and schedule flexibility. Moreover, a total cost of ownership analysis suggests greater financial benefits for commercial vehicle operations, including for freight, than for passenger vehicles (Wadud, 2017), not least because operators are keen to minimise operational costs (Paddeu & Denby, 2022). This might translate in lower rebound effects for freight than passenger transport.

Changes in mileage and modal split due to vehicle automation will have repercussions for road transport's multiple externalities. Our reading of the literature suggests gradients of certainty and consensus. Increases in road safety are widely expected, but Tafidis, Farah, Brijs, and Pirdavani (2022) argue that AVs' potential to enhance road safety will depend on "many factors such as the AVs' characteristics and penetration rate, traffic scenarios, and road network characteristics" (page 262) and that AVs "actual effectiveness will not be known or accurately estimated until sufficient real-world data becomes available" (page 265). Kim, Kim, and Park (2022) concur with regard to trucks, suggesting that the safety benefits of automation will be amplified by the magnitude of damage, injury and fatality these vehicles cause but that claims about benefits are not yet well evidenced. Uncertainty seems somewhat larger for enhanced urban sprawl, given that Harb et al. (2021) report a discrepancy between studies using different research methods: where studies relying on surveys suggest limited changes in residential location choices due to AV adoption and use, simulation studies show considerable urban decentralisation. Nonetheless, uncertainty appears to be largest for AVs impacts on road congestion, physical activity, air pollution and CO_2 emissions. Impacts will depend on the extent of changes to the modal split and VMT as well as the ultimately prevailing ownership models, policy-making, and configuration of transport networks and land uses in specific geographical contexts, especially for passenger transport (Saleh & Hatzopoulou, 2020; Silva, Cordera, González-González, & Nogués, 2022; Spence et al., 2020; Tu, Alfaseeh, Djacadian, Farooq, & Hatzopoulou, 2019).

In short, much uncertainty remains over the likely speed and impacts of widespread AV adoption in future, in both passenger and freight transport. The equivalence in the literature is partly due to differences in research methods used but also reflects uncertainty over how AVs will be adopted and embedded in existing transport systems in particular places. Studies involving professionals may enhance understanding of the various uncertainties identified but should recognise that significant differences in views and expectations may exist within this constituency. Moreover, while passenger and freight transport have different dynamics, actor groups and interests in AV development, they are closely connected with innovation processes informing one another. It is therefore useful to understand these two parts of the transport system in relation to one another.

3. Methodology

3.1. Delphi method

A variety of methodological approaches have been used in research engaging with expert perceptions of AVs. These include quantitative surveys (e.g., Rezaei & Caulfield, 2021; Nogués, González-González, & Cordera, 2020), focus groups (Strömberg et al., 2021), interviews (Botello et al., 2019), Q-method (González-González, Cordera, Stead, & Nogués, 2023; Milakis, Kroesen, & van Wee, 2018) and the Delphi method (Merfeld, Wilhelms, Henkel, & Kreutzer, 2019; Soh & Martens, 2022). These have been used in a variety of ways to understand dis/agreements among participants and to engage with questions of uncertainty. We selected a modified Delphi approach for this research, for reasons described below.

The Delphi method was originally developed by the RAND Corporation in the 1950s (Dalkey & Helmer, 1963) as an exploratory technique that offers insights into "what might be in the future" (Steinert, 2009, page 293), particularly when there is a high degree of uncertainty and "knowledge is contained within a comparatively small pool of experts" (Merfeld et al., 2019, page 69). It is an iterative and flexible method with four common characteristics. It:

- involves several rounds of surveys, often three or four, and increasingly online;
- provides participants with feedback between rounds;
- offers participants the opportunity to modify their responses based on that feedback; and
- provides anonymity for all participants, which makes the approach less vulnerable to the power dynamics and interpersonal relationships that during in-person activities (i.e., workshops, focus groups) often have a strong influence on which voices are heard, diminished or excluded (Mullen, 2003).

Online Delphi studies can use conventional survey platforms (e.g., SurveyMonkey, Jisc Surveys) or a specially designed Delphi platform. The benefit of the latter is that participants can receive real-time feedback (see, Steinert, 2009) and compare their response to others'. Accordingly, we used the Calibrum platform (www.calibrum.com) for the surveys described in this paper, as it offered real-time feedback functionality, and while focused on consensus, was flexibly configured to allow us to nurture dissensus among panel members.

In transport research and other domains, Delphi studies have traditionally been used to build consensus among 'experts' in situations where the future is highly uncertain (see, for example, Schuckmann, Gnatzy, Darkow, & von der Gracht, 2012). Yet, various authors have suggested this constrains the future scenarios that are constructed, and may marginalise more radical imaginings of the future (Soria-Lara & Banister, 2017; Steinert, 2009; Tapio, 2003). While Q-method has historically been used to nurture heterogeneity, this has largely been used for more established topics (Watts & Stenner, 2005). Due to the large uncertainties around AVs, we adopted the dissensus-oriented Delphi approach proposed by Steinert (2009), which cultivates divergence of views, and lends itself to more emergent topics like AVs.

Dissensus can be identified in different ways in a Delphi study. One is to consider the variation around the average or median value for a measure or statement to which participants have responded (Melander, Dubois, Hedvall, & Lind, 2019); the standard deviation and/or interquartile range are then used as indicators of the degree of dissensus. Alternatively, a set of variables can be reduced to underlying dimensions based on participants' responses using factor analysis (Julsrud & Uteng, 2015) or used to segregate participants in mutually exclusive groups with the help of cluster analysis (Tapio, 2003). In this paper, we use both the variation around the average/median value and cluster analysis to identify dissensus within the recruited panel.

3.2. Variables of interest

Our study consisted of three rounds and included quantitative and qualitative lines of questioning, with more open-ended questions asked as the study progressed. The individual rounds had somewhat different foci. All three rounds were focused on potential effects of AVs but approached the topic in slightly different ways. We decided against asking identical questions each round because the Calibrum platform provides real-time feedback to participants (see above) and because we wanted to respond to feedback by participants on earlier rounds and ask more specific questions – for instance, about how automation interacts with electrification and, for passenger transport, a shift towards shared mobility. Each round also included some unique questions. For many questions, participants were asked both what they considered most fitting or appropriate, and how certain they were about their response. Since (technological) futures are inherently uncertain and individuals recognise and respond to (collective) uncertainty in different ways (Sorrentino & Roney, 2000), the uncertainty questions on six-point scales allowed tracking of the degree of uncertainty across the panel and to contextualise individual responses.

Throughout the three rounds, we have deployed the 2018 version of the Society of Automotive Engineer's (SAE) levels of automation to develop a common understanding of what vehicle automation entails. While the SAE levels are not without problems (Hopkins & Schwanen, 2021), we considered a degree of standardisation in the discussion important in light of heterogeneity in conceptualisations of 'automated' vehicles. The SAE levels run from 0 to 5:

- SAE-0: Driver support features, limited to warnings and momentary assistance. Examples include: automatic emergency breaking, blind spot warning, and lane departure warning;
- SAE-1: Driver support features, provide steering OR break/acceleration support. Examples include: lane cantering OR adaptive cruise control;
- SAE-2: Driver support features, provide steering AND break/acceleration support. Examples include: lane cantering AND adaptive cruise control;
- SAE-3: Automated driving features, can drive the vehicle under limited conditions, and only if all conditions are met. Exemplified by traffic jam chauffeuring;
- SAE-4: Automated driving features, can drive the vehicle under limited conditions, and only if all conditions are met. Examples include: local driverless taxi, pedals/steering wheel may or may not be installed; and
- SAE-5: Automated driving features, can drive the vehicle under ALL conditions. Examples include: driverless vehicles which can drive everywhere in all conditions.

For this paper, we concentrate on two sets of issues presented in Section 2: the speed with which AVs are adopted, and their potential impacts. Regarding adoption, we asked participants when they expected 15% of new passenger vehicle and freight vehicle sales to have the different SAE levels of automation. The 15% threshold was selected because it was considered to be a 'middle of the road' scenario similar to those used in scenarios and analyses from KPMG, the UK Society of Motor Manufacturers and Traders (SMMT), among others. Panel members were presented with six timeframes: 2019–2029, 2030–2039, 2040–2049, 2050–2059, 2060 or later, and never. Given that a fair share of current vehicles already meet SAE-1 and SAE-2, the analysis below concentrates on SAE-3, SAE-4 and SAE-5. Uncertainly levels [1 = very uncertain, 6 = very certain] regarding timeframes are also considered. As previous explained, impacts were categorised into motility, mobility, resource implications, and externalities (Table 1).

Since the research project of which the Delphi study is part is concerned with understanding the energy implications of digitalisation in the transport sector, we considered two energy-related impacts in Round I. For the other potential impacts, we have selected the direction of change (decrease/increase) we considered most plausible to minimise the number of questions for participants. To enable direct comparisons between passenger and freight transport we considered the same set of potential impacts for each. In all cases, we asked Round I participants to indicate:

- Likelihood of the potential impact – on a scale from 0 (not likely) to 7 (extremely likely)
- Strength of potential impact – on a scale from 0 (no impact) to 7 (maximum impact)
- Certainty of potential impact – on a scale from 1 (very uncertain) to 6 (very certain)

In Round II we presented the following text, partly informed by the panel's responses to the Round I questions on expected impacts of vehicle automation, to participants:

*While bringing major economic and social benefits, using a car or van contributes to road traffic congestion (excess delays), accidents, physical inactivity, climate change and local noise and air pollution. The UK transport system is emitting a range of harmful air pollutants (*e.g., *CO_2, NO_X, PM), either directly from vehicle operation (*e.g., *tailpipe emissions, non-tailpipe emissions from brake and tyre wear) or indirectly (emissions from fuel/energy production, vehicle manufacturing, maintenance and disposal/recycling).*

We then used a free-text response format to ask participants whether they believe that passenger and freight vehicle automation would respond positively and/or negatively to the challenges mentioned. Moreover, in light of academic literature showing the ownership model to be critically important to the sustainability benefits of vehicle automation in passenger transport (Section 2), we also included questions about four possible impacts of a transition towards shared, automated and electric vehicles (SAEVs). To reduce respondent burden, we narrowed attention to the four potential impacts of increasing accessibility (motility), reducing cost and energy demand (resource implications), and reducing emissions (externalities). Questions focused on the extent of change on a four-point scale [0 = not at all, 3 = a lot] and certainty [1 = very uncertain, 6 = very certain].

Due to the small sample size in the study (see below) we only use simple statistical techniques to examine the quantitative data and thematic analysis for textual data in response to open questions.

3.3. Recruitment and participants

While the term 'experts' is often used for the Delphi method (Sackman, 1975), we purposively worked with the term 'professional' in our study given long-standing criticisms of the meanings and interpretations of 'expertise' (e.g., Mauksh, von der Gracht, & Gordon, 2020). In particular, we sought individuals who worked in a professional capacity in some dimension of automated vehicle innovation. We hoped to have participants from different domains (transport, energy, environment, AI/robotics), sectors (public, private, third) and kinds of road transport (passenger, freight). Initially we set a target of 150 participants for Round I, and took various steps to maximise heterogeneity among the participants in terms of background, experience, sector, and geographical location within the UK. We undertook a detailed stakeholder analysis of organisations to identify the various axes of expertise we wanted represented in the study, identified relevant individuals and collected their contact details (which was very time consuming), and emailed them with a personalised invitation plus a study information sheet and research ethics consent form (as per stipulations of our University).

Recruitment proved extremely challenging (see also Hopkins & Schwanen, 2022), and we were unable to meet our target number. Reasons were variable but included topical fatigue ("Not another AV survey!"), non-identification as a topical 'expert' ("I don't know enough"), uncertainty about methods ("it is impossible to investigate something so uncertain"), and the interrelated issues of lacking time, and professional or personal pressures. We decided to stick to our original intention to recruit on the basis of heterogeneity and diversity and refrain from reaching out to our own personal networks – characterised by considerable homophily – to reach the target of 150. In other words, we did not place calls on social media or (academic) listservs, and terminated a long-winded recruitment process of over 12 weeks after we were unable to gather additional participants for Round I.

We managed to recruit 25 participants for Round I, have 15 in Round II, and only four in Round III. On many levels this is a disappointing outcome, particularly in the context of the effort and time expended, but our Round I sample is reasonably diverse (Table 2). While women are underrepresented, and all participants are highly educated, there is good diversity in terms of participants' expertise, sector, line management responsibilities (as indicator of seniority) and age. The level of diversity is somewhat lower for Round II, with area of expertise becoming limited to transport and energy. Nevertheless, geographical orientation and domain of expertise remain evenly spread across categories for Round II.

Moreover, our sample is not an outlier in Delphi research, with Shariff (2015, p. 3) recognising the variations in possible sample sizes for Delphi-based research, with Delphi studies not calling "for a representativeness of the sample in terms of statistical purposes; therefore, sample size principles differ from those in other surveys". For Birko, Dove, and Özdemir (2015), a sample size range of 6 to 50 experts can be used for Delphi surveys. de Villiers, de Villiers, and Kent (2005) suggest the variation comes down to the composition of the expert panel, and the aims of panel selection. Skulmoski, Hartman, and Krahn (2007) review the diversity of applications of Delphi research, and in their table show how one-, two-, and three-round Delphis are all common, along with sample sizes that include: 3 (across 3 rounds; Lam, Petri, and Smith (2000)) and 4 (across 2 rounds; Gustafson, Shukla, Delbecq, and Walster (1973)) and 9 (across 3 rounds; Wynekoop and Walz (2000)). Such figures have long been reported in transport studies, for instance with Morley English and Kernan (1976) reporting samples of 12 (r1) and 11 (r2), and then 16 (r1) and 12 (r2) in their Delphi examining air travel and aircraft technology development. The use of two-round Delphis is common, particularly with smaller sample sizes. For instance, Karamperidis & Valantasis-Kanellos (2022) had a sample of 29 for r1 and then 12 for r2. Our study, with 25, 15 and 3 for the first, second and third round, respectively fits within these ranges, and the addition of the third

Table 2
Composition of the Delphi panel[1].

			Round I ($n = 25$)	Round II ($n = 15$)
		Business	20%	27%
		Consultancy	20%	20%
	Sector	Government	8%	–
		Academic	24%	27%
		Third sector	8%	–
		0- < 2 years	16%	7%
Current organisation		2- < 5 years	16%	20%
		5- < 10 years	24%	20%
	Time employed	10 or more years	24%	27%
		None	36%	40%
		1–3 persons	20%	20%
		4–8 persons	8%	7%
		9–29 persons	8%	–
	Line management responsibilities	30+ persons	8%	7%
		Passenger transport	32%	27%
		Freight transport	20%	20%
	Area	Energy	8%	7%
		Environment	12%	–
		Robotics/AI	8%	–
		Other	24%	20%
		Technical/engineering	24%	27%
		Policy	20%	13%
Expertise		Social science	12%	13%
	Domain	Other	24%	20%
		England	36%	33%
		Scotland	24%	20%
		Wales	24%	20%
		North Ireland	12%	7%
		UK-wide	12%	33%
		Global	26%	40%
	Geographical orientation	Urban	40%	33%
		Undergraduate degree (or equivalent)	28%	20%
		MA/MSc degree	12%	7%
	Highest educational qualification	PhD/doctorate	36%	40%
		Below 40	32%	33%
	Age	Over 40	40%	33%
		Men	56%	47%
Background	Gender	Women	16%	13%

[1] Percent scores per variable may not add up to 100% because of missing information.

round allows us – albeit modestly – to further interrogate the perceptions of the panel.

4. Speed of adoption

The time at which Round-I participants expect that 15% of new passenger vehicles sold will be automated increases as the level of automation is higher (Table 3). At the same time, the degree of consensus regarding the most common timeframe and level of certainty tend to decrease with the SAE level. Thus, smaller changes in the demands placed on automation of the driver task in passenger vehicles are expected to happen more quickly and tend to generate less controversy among participants. There is, however, one exception that disrupts correlation between speed of adoption and degree of automation: a small number of participants is convinced that SAE-3 will never reach a 15% market share, presumably because of the burdens it places on 'drivers' when unusual situations demanding their attention occur.

The patterns for freight vehicles are broadly comparable with those for passenger transport: smaller changes compared to the current norm are expected to happen earlier and are characterised by greater consensus and certainty. The main difference is that the modus, or most frequent number in the sequence, falls later in time for SAE-5: 2050–2059 for freight vehicles against somewhere in 2030–2049 for passenger vehicles. This is the main suggestion in the Round-I data that the trajectory of AV adoption may differ between passenger and freight transport.

Dissensus is articulated in two ways among the responses. Not only does the spread across time periods increase as SAE levels go up; it is also possible to identify three rather distinct visions on speed of adoption. A hierarchical cluster analysis using Ward's algorithm and all 12 variables in Table 3 identifies three sets of expectations regarding AV uptake. The first we call *Fast and Confident* and is characterised by strong confidence in AVs at all three SAE levels having reached a 15% market share by 2040. This vision is most common among younger (<40 years) and female participants and/or those with professional expertise outside urban transport. The second set of expectations, *Most Uncertain* (MU), stands out because of the high level of uncertainty but tends to occupy the middle ground between the other two clusters in terms of when 15% market shares in passenger transport will be reached. Participants in this cluster are older (>40 year), male, often working in academia and holding a PhD and/or with experience at the global level. Finally, the *Most Sceptical* (MS) expectations gathers most scores in the 'never' category and falls in-between the other vision in terms of uncertainly levels. This set of expectations is also characterised by the clearest difference in adoption between passenger and freight transport, with the latter expected to reach a 15% market share marginally ahead of the former across SAE levels. The eight participants gathered in the MS cluster are close to the overall profile of the panel (Table 2) although they are slightly more likely to be male and have expertise in urban transport, typically within England and outside passenger transport.

5. Impacts in passenger transport

There are marked differences in the expected likelihood, strength and certainty of effects of automation on passenger transport across the Round-I participants. Table 5 shows that likelihood and strength are highest in the mobility and externalities categories, with increased VMT and greater road safety at the top, followed by the decreased use of other modes. The prominence of increased VMT among the whole set of potential impacts indicates that the panel collectively expect vehicle automation in passenger transport to generate both direct rebound effects and a reinforcement of automobility. On the other side of the spectrum, increases in vehicle ownership are least expected (yet also characterised by the strongest uncertainty), followed by reductions in out-of-pocket costs and energy demand. Certainty levels vary considerably less than those for likelihood and strength, both across impacts and across participants for a given impact.

Based on standard deviation and interquartile range (IQR) values in Table 5, dissensus within the panel is starkest for the likelihood of increased congestion as well as the strength of increased energy use, accessibility and vehicle ownership. On the whole, dissensus levels are slightly greater for strength than for likelihood of potential impacts. Dissensus within the panel also becomes apparent when a cluster analysis is conducted on all 39 Round-I variables in Table 5. This generates three sets of expectations regarding AV impacts (Fig. 1A-D), which we label these as: 1) Enhancing Unsustainability, 2) Contributing to Environmental Sustainability, and 3) Foregrounding Uncertainty.

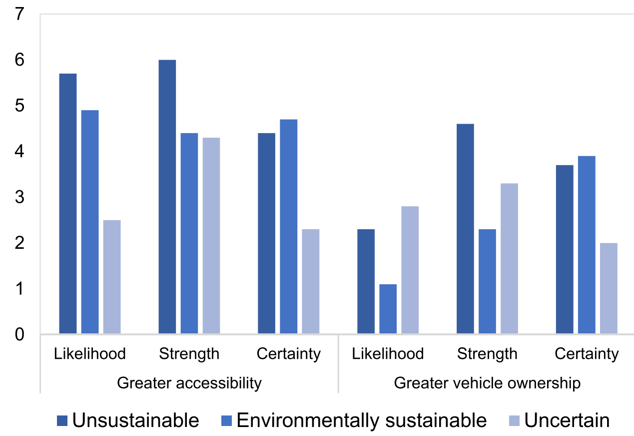
Enhancing Unsustainability (EU) brings together seven participants representing the unsustainable dimensions of vehicle automation in Round I. In their view, the adoption of vehicle automation in passenger transport will enhance accessibility but also increase vehicle mileage, decrease use of non-car modes and (therefore) increase road congestion, diminish physical activity and enhance urban sprawl. This set of expectation is more common among men, over-40s, academics, those with some level of seniority within their respective organisations, and/or those with technical/engineering expertise.

Various answers to the Round II open-ended question about impacts (Section 3.2) help to elaborate the expectations gathered in EU. One academic explained that "until the automation functionalities explicitly target emissions (which they do not, at the moment), the induced demand that automation will bring about will increase emissions". Another participant suggested that.

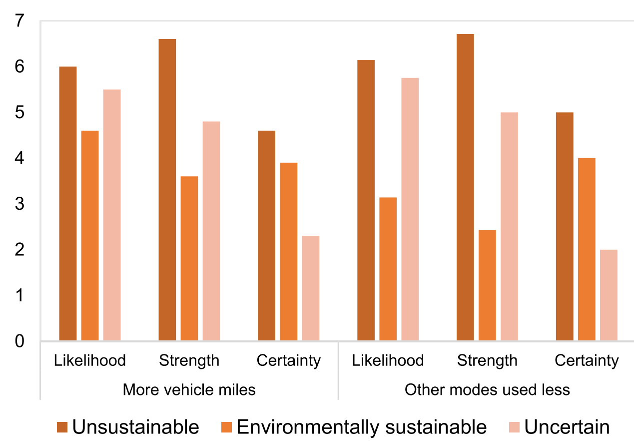
if AVs do indeed succeed in increasing mobility (for example for the disabled and the elderly), there may be a higher demand for vehicles and therefore congestion and pollution. Increasing the efficiency of fuel consumption and travel etc. *could also result in a negative effect due to the*

Table 3
Expected time at which 15% of new sales will be AVs and associated level of certainty.

		Timing (% within SAE level)						Certainty (% within SAE level)					
		2019–2029	2030–2039	2040–2049	2050–2059	2060 or later	Never	Very uncertain	Un-certain	Slightly uncertain	Slightly certain	Certain	Very certain
Passenger	SAE-3	41.7	25.0	12.5	4.2	0.0	16.7	8.3	12.5	20.8	25.0	25.0	8.3
	SAE-4	12.0	40.0	32.0	8.0	0.0	8.0	8.0	16.0	24.0	20.0	28.0	4.0
	SAE-5	8.0	24.0	24.0	20.0	16.0	8.0	16.0	16.0	16.0	32.0	20.0	0.0
Freight	SAE-3	50.0	25.0	16.7	0.0	0.0	8.3	12.5	16.7	16.7	12.5	33.3	8.3
	SAE-4	16.7	41.7	12.5	29.2	0.0	0.0	8.3	25.0	12.5	33.3	16.7	4.2
	SAE-5	12.5	20.8	16.7	29.2	8.3	12.5	8.3	25.0	16.7	33.3	16.7	0.0



A. Increasing accessibility and vehicle ownership



B. Increasing vehicle miles and diminishing use of other modes

Fig. 1. Mean values for likelihood, strength and uncertainty for potential impacts of vehicle automation on passenger transport.

Jevons Paradox.

Both responses echo prior studies (Section 2) by suggesting that rebound effects in the form of extra VMT may overshadow potential beneficial impacts such as reduced congestion, carbon emissions and air pollution.

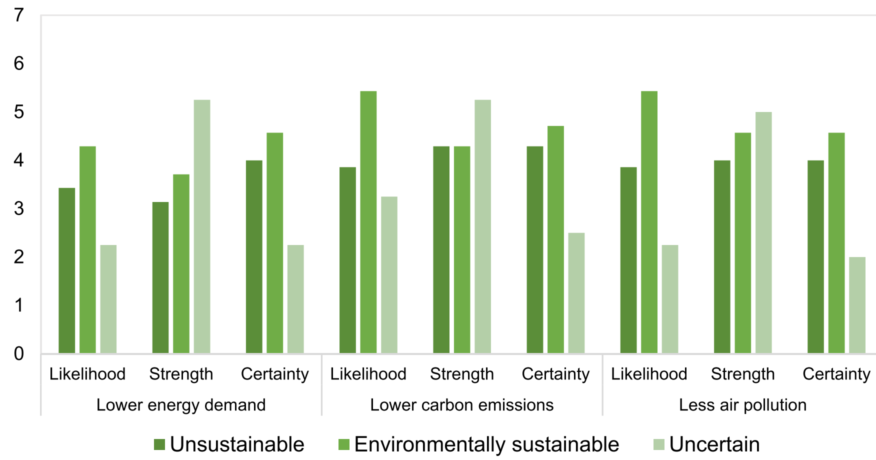
The expectations gathered in *Contributing to Environmental Sustainability* (CES) foreground AVs' potential environmental benefits in passenger transport. The seven proponents appreciate the likelihood of both greater VMT and a modal shift towards vehicles, but tend to view these effects as relatively weak or mild and are more cautious about how automation may enhance vehicle-based motility than those in EU. They are also most optimistic about AVs' potential to reduce energy demand, contribute to carbon reduction targets and diminish air pollution from transport. This is aptly illustrated by the response to the Round-II open-ended question (Section 3.2) that "there will be improvements in regular driving to adopt a more fuel-efficient style and a reduction on collisions will reduce overall congestion" from a consultant in this group. The profile of CES protagonists is rather diffuse but there is a slight over-representation of younger (<40 years) participants and/or those working in a private sector business, including consultancy.

Foregrounding Uncertainty (FU) stands out because of comparatively strong uncertainty about what effects passenger vehicle automation may generate. A small group of four participants are distinguished from the other two because they are consistently much more uncertain about what effects vehicle automation might have, although their views on likelihood and strength of potential impacts tend to fall between the other two groups. It is difficult to characterise individuals in this cluster but women, older participants and academics with PhDs appear somewhat over-represented. Overlap with the MU group for the speed of AV adoption is more limited than might be expected.

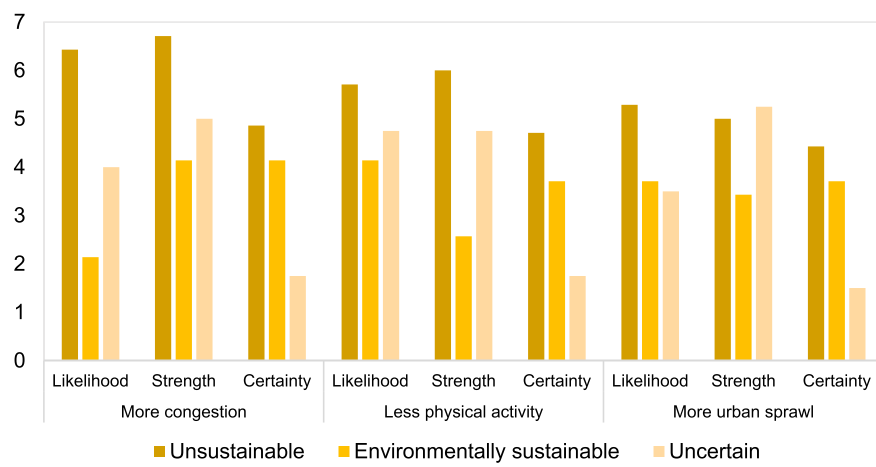
Further analysis of the textual responses to the Round-II open-ended questions showed two findings that the remained largely invisible in the cluster analysis on the quantitative Round-I data. One revolves around *contingency*: various participants, particularly those associated with FU, expected the impacts of automation in passenger transport to depend on the context – as per the wider academic literature (Section 2). They highlighted the relevance of place of deployment, policy and concurrent sociotechnical innovations. An EES proponent who works in a commercial research organisation believe that automation of passenger vehicles.

has the potential to be a positive response as they will be increasingly required to operate in cities implementing air quality or clean air management zones. … However, automation may be confined to specific, highly instrumented, routes rather than the entire route network which may involve cross boundary routes.

The role of policy is similarly put forward by a local government employee: "[t]he impact [of vehicle automation] will depend on the associated policies and whether ride share and usership (potentially positive) is prioritised above the ability to simply replace driven with driverless (potentially negative)". The quotation also emphasises the



C. Reducing energy demand, carbon emission and air pollution



D. Enhancing congestion, reducing physical activity and increasing urban sprawl

Fig. 1. (*continued*).

importance of the AV ownership model, as per the literature (section 2), and other innovations. Vehicle electrification was also mentioned in this context. As one CES protagonist working for the Government indicated, “In the short to medium term the primary source of benefits are likely to be caught up in the broader story on the electrification of transport”.

The relevance of thinking about vehicle automation in conjunction with the vehicle ownership model and electrification is also suggested by the responses to the Round-II questions about SAEVs (Table 6). Comparing Tables 5 and 6 is not straightforward, among others because fewer potential impacts are included. To minimise respondent burden, we focused the questions about SAEVs on those impacts for which the literature suggested strong ambiguity (accessibility, costs) and which related to the aims of the wider research programme of which this study is part (energy demand, emissions). Careful consideration of each indicates that expectations around monetary cost reduction tend to increase when the focus shifts from automation in general to SAEVs. The average of 2.7 for the latter is closer to ‘a lot’ [3] than to ‘somewhat’ [2] and arguably above the averages of 2.9 for likelihood and 3.4 and strength, both measured on a scale from 0 to 7, in Table 5. This difference is compatible with the hypothesis that SAEV may trigger less direct rebound than automation in general. Nonetheless, Table 6 also suggests that SAEVs' impacts in terms of reducing energy demand and emissions may not be much greater than of vehicle automation in passenger transport in general. Interestingly, the levels of both dissensus and uncertainty regarding the specified impacts tend to be greater for SAEV than automation. This may be because SAEVs are a more radical innovation than privately owned AVs, be they electric or not, which makes SAEVs' potential impact more challenging to gauge. Because the small number of participants answering the questions in Table 6 ($n = 11$), results are not disaggregated according to the three visions about impact introduced above. Nonetheless, there is a tendency in the data for EES proponents to be slightly more optimistic about the extent of reduced energy demand and emissions, and those supporting FU to articulate the highest level of uncertainty about SAEV impacts.

The second finding emerging from the analysis of textual Round-II responses centres on *ambiguity*. The impacts considered in the Delphi study are sometimes in tension with one another, and different affective dispositions may be shaping participants' thinking when evaluating what might happen, sometimes almost simultaneously. Both these points can be gleaned from the detailed answer in Round II by an academic whose Round-I responses helped to constitute FU (emphasis in original):

My hope is that vehicle automation will improve road safety for both vehicle occupants and other road users. Vehicle automation might allow cars to travel closer together at higher speeds, therefore increasing efficiency and possibly reducing congestion. However, there will also be negative consequences of this: more cars on the road = more pollution. The easier we make it to travel by car, the more people will do it, for more journeys - consequences *will be higher levels of [physical] inactivity. … There will be positive and negative consequences of the changes, but I'm not sure that they will all be INTENDED consequences.*

Over the course of the response, their affective disposition changes, from hope to something resembling resignation (from 'However' onwards). Assessment of what effects vehicle automation in passenger transport might generate is no 'cold' and rational assessment probabilities, magnitudes and degrees of confidence but a process in which different factors, beliefs and sentiments jostle for position and are somehow synthesised in ways that can differ across individuals, questions and moments. Mixing question formats in a Delphi study can begin to show some of this complexity in ways that quantitative scores as summarised in Tables 3-4 on their own are unlikely to achieve.

6. Impact in freight transport

There are also clear differences in the expected likelihood, strength and certainty of effects of automation on freight transport in Round I, although different impacts are anticipated to be important compared to passenger transport. Likelihood and strength are again highest in the externalities category, followed this time by resource use and mobility (Table 7). Across Rounds I and II, the expected level of (direct) rebound is lower for freight than for passenger transport. It seems that, in the words of one Round-II participant, this reflects different responses to changes in (generalised) costs among decision-makers, as suggested in previous studies (Section 2):

Similarly to passenger vehicle automation, there may be an increase in freight being transported, especially if freight vehicle automation results in a cost reduction, however it is less elastic than personal travel, so this effect is not expected to be as significant.

In Round I, effects on motility and on the externalities of physical activity and urban sprawl were expected to be rather unlikely and much weaker than for passenger transport. More generally, a comparison of Table 7 with 5 indicates that the differences in likelihood and strength are much more pronounced across impacts for freight than for passenger transport, suggesting that a smaller set of impacts is expected. The most likely and strongest impact occurs again for road safety, with average scores almost identical to those for passenger transport (notwithstanding slightly less consensus about the strength of this impact for freight). Interestingly, reductions in carbon emissions and air pollution are ranked joint second for freight, with scores largely above those for passenger transport. To some extent this may reflect differential impacts on resource use, given that automation is more likely to reduce costs and energy consumption in freight, while the strength of these impacts is also anticipated to be somewhat larger. The certainty of impacts is of a similar level in both freight and passenger transport.

In terms of dissensus, Table 7 indicates this is strongest for, again, traffic congestion yet also for increase in vehicle miles. For both likelihood and strength, the standard deviation and IQR are largest for the latter impact. This suggests that direct rebound effects for vehicle automation in freight are more contested than in passenger transport within our panel.

The differentiated views on vehicles miles and congestion are also evident from the cluster analysis conducted on all 39 questions on likelihood, strength and certainty of different impacts of vehicle automation in freight in Round I (Fig. 2). Three sets of expectations regarding future impacts can again be constructed: 1) Enhancing Sustainability, 2) Mostly Enhancing Sustainability, and 3) Uncertain and Enhancing Unsustainability.

Enhancing Sustainability (ES) emerges from the responses of five participants who are very positive about the impacts of automation in freight transport (Fig. 2A-D). They expect negligible effects on motility and consider VMT rebound effects and modal shift towards vehicular mobility unlikely and small. Anticipated cost reductions may be comparatively modest but reductions in energy demand, carbon emissions and pollution are small. Neither more congestion nor greater urban sprawl are expected. As two protagonists explained in Round II, automation in freight leads to "longer periods of vehicle use, achieving logistics [g]oals off-peak and with a more efficient driving style" and to "[l]ess congestion and emissions". Profiling proponents of the ES vision is difficult because of the small numbers. The most distinctive aspect is that they are almost exclusively male.

Mostly Enhancing Sustainability (MES) is in many ways close to ES, although its seven protagonists are slightly less outspoken on the environmental benefits and believe that monetary cost reductions will be greater than their ES counterparts expect (Fig. 2B, D). The biggest difference is, however, that expectations in MES suggest that vehicle automation in freight will generate substantially more miles travelled and congestion (Fig. 2A, C). MES is therefore characterised by greater ambiguity than ES. An academic associated with MES elaborated this ambiguity in Round II as follows:

Positively, in the sense that vehicle automation functionalities will likely include reduction of emissions as an objective (as for passengers). Negatively, as vehicle automation will likely drive freight transport away from more environmentally-friendly modes, such as rail and inland shipping.

Finally, *Uncertain and Enhancing Unsustainability* (UEU) is substantially different from the other two sets of expectations. As Fig. 2 shows, it is first and foremost characterised by considerable uncertainty: across the impacts considered, the average score for the uncertainty items consistently falls around 2, or 'uncertain'. Proponents of this vision are also least optimistic about benefits brought by vehicle automation in freight. They expect substantially greater energy use and urban sprawl than participants gathered in ES or MES. They also think that increases in traffic safety and reductions in monetary costs, carbon emissions and air pollution are considerably less likely. Since the average scores on the likelihood items for more vehicle miles, congestion, energy use and sprawl are higher than for increased safety and reduced cost, carbon missions and air pollution, UEU foregrounds the potential for

Table 4
Expected time at which 15% of new sales will be AVs and associated level of certainty.

		Timing						Certainty					
		SAE-3 pass.	SAE-4 pass.	SAE-5 pass.	SAE-3 freight	SAE-4 freight	SAE-5 freight	SAE-3 pass.	SAE-4 pass.	SAE-5 pass.	SAE-3 freight	SAE-4 freight	SAE-5 freight
Fast & Confident (*n* = 9)	Mean	1.1	1.8	2.0	1.4	1.5	1.8	4.8	4.5	4.1	5.0	4.4	4.1
	Median	1	2	2	1	1.5	2	5	5	4	5	4	4
	S.D.	0.4	0.5	0.8	0.5	1.1	0.7	0.9	0.8	0.6	0.5	0.5	0.6
Most Uncertain (*n* = 7)	Mean	2.4	2.9	3.9	1.8	3.2	4.2	2.8	2.3	1.9	2.7	2.0	2.0
	Median	2	3	4	2	3	4	3	2	2	3	2	2
	S.D.	1.5	0.6	0.8	0.8	0.8	1.0	1.0	0.8	0.8	1.3	0.7	0.7
Most sceptic (*n* = 8)	Mean	4.0	3.7	4.4	3.0	2.9	4.1	3.7	4.4	4.3	3.3	4.0	3.9
	Median	4	3	5	3	2	4	4	4	4	3	4	4
	S.D.	2.1	1.7	1.5	2.2	1.1	1.5	1.7	1.0	0.8	1.8	1.3	1.1

Timing: 1 = 2019–2029, 2 = 2030–2039, 3 = 2040–2049, 4 = 2050–2059, 5 = ≥2060, 6 = never.
Certainty: 1 = very uncertain, 2 = uncertain, 3 = slightly uncertain, 4 = slightly certain, 5 = certain, 6 = very certain.

Table 5
Expected impacts of vehicle automation in passenger transport.

	Likelihood of impact [0,7]					Strength of impact [0,7]					Certainty of impact [1,6]				
	Mean	SD	1Q	Med	3Q	Mean	SD	1Q	Med	3Q	Mean	SD	1Q	Med	3Q
Motility															
⇧ accessibility	4.4	2.2	3	5	6	4.4	2.2	2.5	5.5	6.8	4.1	1.2	3	4	5
⇧ ownership	1.9	1.6	0	2	3	3.3	2.3	1	3	5	3.4	1.4	3	4	4
Mobility															
⇧ vehicle miles	5.1	2.1	5	6	7	4.8	2.2	3	6	7	3.7	1.4	3	4	5
⇩ use of other modes	4.8	2.1	4	5	7	4.6	2.2	3	5	7	3.8	1.7	3	4	5
Resource use															
⇩ costs	2.9	2.0	1.5	2	4	3.7	2.0	2	3	5	3.9	1.2	3	4	5
⇩ energy demand	3.6	1.9	2	3	5	4.0	2.0	2.3	4	6	3.8	1.2	3	4	5
⇧ energy use	4.1	2.1	3	4	6	4.2	2.3	2	4	7	3.6	1.3	3	4	4
Externalities															
⇧ road safety	4.9	2.0	3.5	5	7	5.7	1.3	5	6	7	4.3	1.3	3.5	4	5
⇧ traffic congestion	4.2	2.5	2	5	7	5.3	2.0	5	6	7	3.8	1.5	3	4	5
⇩ carbon emissions	4.3	1.8	3.5	4	5.5	4.7	1.9	4	5	6	4.1	1.1	3	4	5
⇩ air pollution	4.1	1.9	2.5	4	5.5	4.6	2.1	3.3	5.5	6	3.8	1.2	3	4	5
⇩physical activity	4.8	1.9	4	5	6	4.3	2.1	3	4	6	3.7	1.6	3	4	5
⇧ urban sprawl	4.3	1.8	3	4	5	4.5	2.0	3	5	6	3.5	1.4	3	4	4

Table 6
Expected impacts of shared, electric and autonomous vehicles in passenger transport.

	Extent of impact [0,3]					Certainty of impact [1,6]				
	Mean	SD	1Q	Med	3Q	Mean	SD	1Q	Med	3Q
Motility										
⇧ accessibility	2.1	1.1	1	3	3	2.7	1.3	1.8	3	4
Resource use										
⇩ costs	2.7	1.3	1.8	3	4	2.4	1.5	1	3	4
⇩ energy demand	1.5	1.0	1	1	2	2.9	1.3	3	3	4
Externalities										
⇩ emissions	1.7	1.0	1	2	2	3	1.3	3	3	4

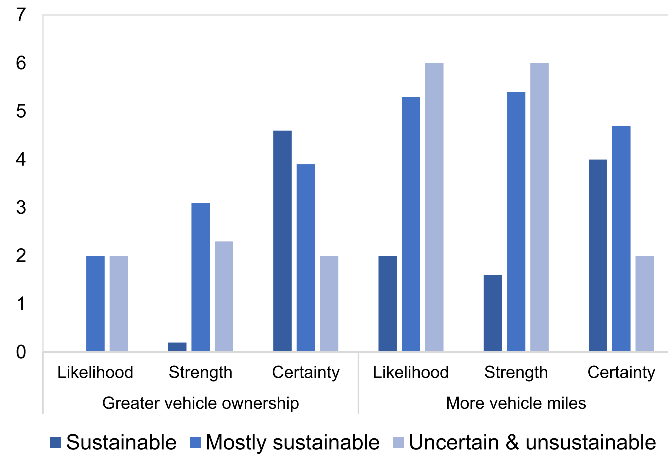
Table 7
Expected impacts of vehicle automation in freight transport.

	Likelihood of impact [0,7]					Strength of impact [0,7]					Certainty of impact [1,6]				
	Mean	SD	1Q	Med	3Q	Mean	SD	1Q	Med	3Q	Mean	SD	1Q	Med	3Q
Motility															
⇧ accessibility	2.5	2.1	1	2	4	2.3	2.1	1	1.5	3.8	3.9	1.2	3	4	4.5
⇧ ownership	1.3	1.3	0	1	3	1.8	2.0	0	1	3	3.8	1.5	2.8	4	5
Mobility															
⇧ vehicle miles	4.1	2.6	2	5	7	3.9	2.6	1	4	6	4.2	1.4	2.75	4	5
⇩ use of other modes	4.5	2.2	3	5	6	4.2	2.3	2	4	6	4.0	1.3	3	4	5
Resource use															
⇩ costs	4.2	2.2	3	4	6	3.9	2.1	2	4	6	4.3	1.5	3	4	5.5
⇩ energy demand	4.6	2.2	3	5	6	4.6	2.2	3	5	6	4.2	1.4	3	4	5
⇧ energy use	3.1	2.2	1	3	5	3.3	2.2	1	3	5					
Externalities															
⇧ road safety	5.0	2.0	4	5	7	5.6	1.6	4.3	6	7	4.3	1.6	3	4	6
⇧ traffic congestion	3.3	2.5	1	3	5	3.6	2.1	2	4	6	3.6	1.3	3	4	5
⇩ carbon emissions	4.7	2.2	4	5	7	5.2	2.1	5	6	6.8	4.3	1.4	3.5	5	5
⇩ air pollution	4.7	2.2	4	5	7	5.0	2.3	4.3	6	6.8	4.3	1.4	3	5	5.5
⇩physical activity	1.9	2.1	0	1	4	2.0	1.9	0	1.5	3.3	4.1	1.5	3	4	5
⇧ urban sprawl	2.0	1.7	1	1	3	2.0	1.8	1	1	3	3.7	1.5	3	4	5

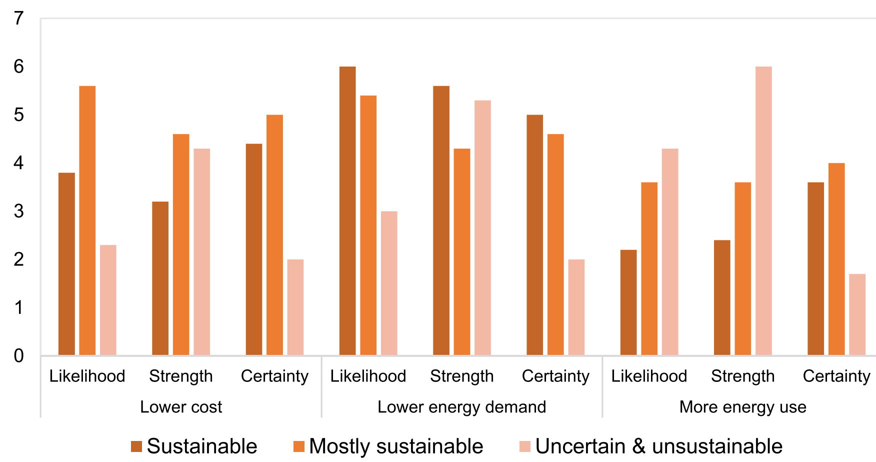
unsustainable consequences of vehicle automation in freight.

At the same time, only three participants support UEU, all of whom are gathered under FU for passenger transport. Their expectations regarding vehicle automation in freight transport are at least in part driven by the prospect of modal shift towards vehicular transport and rebound effects. One consultant explained in Round II that “there is a risk that automated vehicles may take traffic off other low emission modes such as rail or water”, while an academic suggested “more obvious benefits than [for] passenger vehicles in terms of efficiency (platooning, etc.), although having more road freight is overall bad for the environment”. This response resonates with the quantitative analysis of the Round-I data by suggesting that benefits of vehicle automation tend to be larger, or at least more obvious, for freight than for passenger transport. Another source of high levels of uncertainty among UEU protagonists lies in the significance of contingency, and the need to think about automation in conjunction with other technological changes. The consultant who has already been quoted remarked that the impact of vehicle automation “depends [on] whether we are able to solve the [energy] generation mix to be carbon free, and also resolve issues around battery recycling and pollutants”.

The tendency to contrast impacts of vehicle automation in freight transport with those in passenger transport was not limited to the



A. Increasing vehicle ownership and vehicle miles



B. Reducing costs, reducing energy demand and increasing energy use

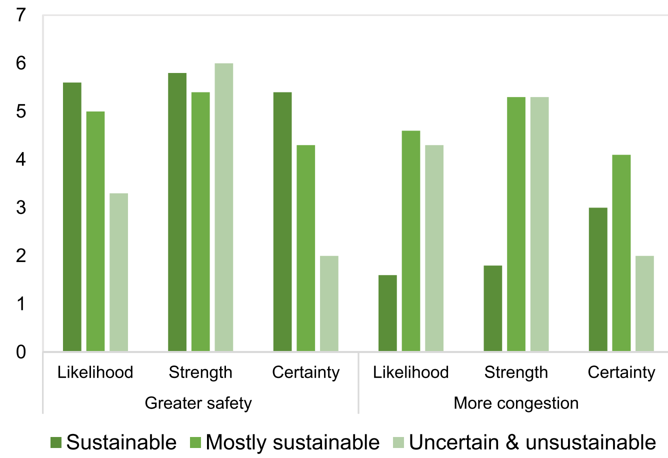
Fig. 2. Mean values for likelihood, strength and uncertainty for potential impacts of vehicle automation on freight transport.

academic linked with UEU. As the quotation at the beginning of this section already suggested, other participants did the same in their Round-II responses. They thus highlight several specific aspects of freight vehicle automation that demand consideration in thinking about potential impacts. An obvious specificity is the potential for vehicle platooning, already referenced by the aforementioned consultant, and also brought out by another participant: "[t]he opportunity to platoon longer journeys, and use consolidation/last effectively could have a positive impact".

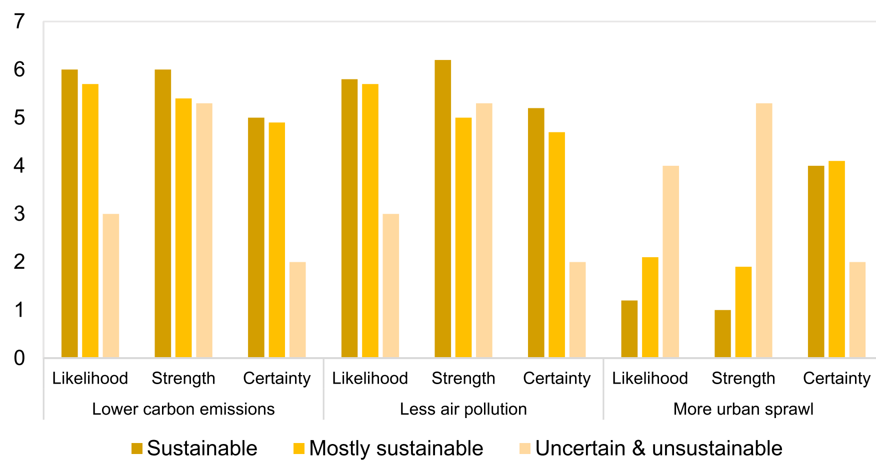
Other specificities relate to freight vehicles being part of broader logistics chains and being subject to a 'bottom line' – with due consequences for potential impacts because of uncertainty about adoption. On one hand, vehicle automation was positioned as "toys and gadgets" for which there is "unlikely to be [a] serious [market] in such a financially competitive industry" as the freight sector. On the other, a private-sector ES protagonist indicated that "uptake" of vehicle automation in freight transport "is more likely to be driven by bottom-line questions on the relative cost of a CAV [connected and autonomous vehicle] and conventional vehicle with driver than broader socio-environmental concerns. It may be seen as counter-intuitive but this could lead to faster uptake" and thus generate impacts that are positive from an environmental sustainability perspective. An MES protagonist from the private sector drew attention to distributional issues and place of deployment, arguing that vehicle automation in freight "may only be adopted by the larger fleet operators rather than the owner/operators and is potentially confined to specific freight routes that are able to support automated vehicles".

7. Conclusions

This paper has analysed the expectations of a small group of UK-based professionals in transport, energy, environment and AI/robotics about the time of adoption of vehicle automation and the impacts this may generate in both passenger and freight transport. A three-round dissensus Delphi study was conducted in which attention was directed to not only when 15% of new vehicles will be automated at a certain SAE level or how likely and strong particular impacts may be, but also how certain participants were about their answers. Recruitment proved to be genuinely challenging, with only 25 professionals participating in the first round and considerable attrition in the two subsequent rounds, despite extensive effort to increase participation throughout the study. As a result, we cannot claim that our findings are in any way representative of what relevant professional communities across the UK expect regarding vehicle automation, and stress their exploratory character. While the small number of participants is a shortcoming, we do believe our findings and approach are worth sharing and



C. Increasing road safety and road congestion



D. Reducing carbon emissions, reducing air pollution and increasing urban sprawl

Fig. 2. (*continued*).

communicating, if only as an exploratory study and because the questions and analysis are worth replicating with a much larger, and preferably, international panel. Such a project might also find more active ways to make use of the real-time feedback, and monitor the ways the panel uses this feature (or not), particularly if multiple time zones are included. Future researchers would also be encouraged to think carefully about recruitment of the panel and the challenges between open calls for participants verses the selection of panel members, both with very real limitations (see Hopkins & Schwanen, 2022). With caution and reservations, we draw three sets of conclusions from our analysis.

First, with respect to time of adoption, there is both con- and dissensus in our panel. Broad agreement exists about linearity of adoption, with strong similarity between passenger and freight transport: the more automated vehicles diverge from what is currently normal, the later in the future a market share of 15% of new vehicles will be reached. Yet, there is extensive dissensus in all of the three dimensions highlighted in our questions: level of automation, moment when 15% of new vehicle sales is automated, and un/certainty about that moment. The descriptive analysis highlighted how participants are most divided on when 15% of new vehicles will meet the SAE-5 standard. Using cluster analysis, we have identified three sets of expectations regarding adoption that can be placed on two axes capturing the degrees of optimism, from adoption happening soon (*Fast & Confident*) to being far away or occurring never (*Most Sceptical*), and certainty, from high (*Fast & Confident*) to low or very low (*Most Uncertain*).

Second, the analysis of expected impacts of passenger vehicle automation has highlighted the possibility of considerable direct rebound effects and a strengthening of automobility. While increased traffic safety was seen as the main benefit, this was closely followed by greater VMT and a shift from other modes to car use. There was, however, substantial dissensus regarding the changes vehicle automation in passenger mobility may generate. Whether such automation will enhance congestion, and by how much, was a moot point. The three visions identified using cluster analysis can again be organised along the two axes of certainty (high in *Foregrounding Uncertainty*, lower in the other two) and optimism, here about the environmental impacts of passenger vehicle automation. Both *Enhancing Unsustainability* (EU) and *Contributing to Environmental Sustainability* (CES) recognise the potential for more car use with vehicle automation, albeit the latter less so than the former. Yet the key difference between the visions is that EU proponents are more convinced this extra car use will lead to more congestion, physical inactivity and urban sprawl. They are also less optimistic than CES protagonists that passenger vehicle automation will reduce energy demand, air pollution and carbon emissions. To an extent, then, our panel reproduces the controversies over the potential environmental impacts of passenger vehicle automation that have been reported in Lyons (2022) and the studies reviewed in Section 2.

Our analysis has echoed previous studies in highlighting the relevance of context to the potential impacts of passenger vehicle automation, with place of deployment, government policy and relationship with other sociotechnical innovations expected to play an important role. At the same time, and in contrast to much of the literature reviewed in Section 2, Round II of our Delphi study did not suggest that participants were markedly more positive or certain that shared, automated and electric vehicles (SAEVs) will have more beneficial impacts from a sustainability perspective than automated vehicles more generally. As with the moment at which at least 15% of new vehicles meets SAE-5 requirements, the uncertainty over SAEVs' benefits seems to reflect the extent of difference vis-à-vis to current passenger vehicles and ownership regimes.

Third, the impacts the panel expected for vehicle automation are quite different between passenger and freight transport. For the latter, greater road safety is again expected to be the biggest benefit, there are again three sets of expectations that can be positioned along axes of certainty and optimism about environmental impacts, and context will again matter to what impacts will ultimately materialise. However, the panel expected direct rebound effects to be substantially smaller on average, and are a greater source of dissensus than with passenger transport. Freight vehicle automation is also expected to generate bigger benefits in terms of air quality and climate change mitigation. This is reinforced in the cluster analysis where the two prevailing visions suggested that automation of freight is at least 'mostly' enhancing sustainability, and only a small minority of participants was shown to see that innovation through the prism of (mostly) unsustainable impacts. According to participants, the differences in expected impacts between passenger and freight transport reflect starker minimisation of financial costs in decision-making about the use of freight vehicles and the competitiveness of the freight and logistics section. This finding resonates with conclusions in Wadud (2017) and Paddeu and Denby (2022). Our findings imply that more research needs to be directed towards how automation in freight transport will play out and what changes it might generate.

Automation of passenger and freight vehicles may not happen at the speed that was expected in the mid-2010s, but can reasonably be expected to generate an array of benefits. If and how it will help to make transport more sustainable remains a question of deep uncertainty, with at the least the professionals in our study unable to agree on what changes in mobility, resource use and externalities this sociotechnical innovation may bring. This, together with the ongoing innovation process, makes replication of the current study with larger and more diverse samples a worthwhile exercise.

CRediT authorship contribution statement

Debbie Hopkins: Conceptualization, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Tim Schwanen:** Funding acquisition, Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

We have no conflict of interest to report.

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