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Fully automated vehicles: A cost-based analysis of the share of ownership and mobility services, and its socio-economic determinants

Zia Wadud (Z.Wadud@leeds.ac.uk) and Giulio Mattioli (giulio.mattioli@tu-dortmund.de)

Abstract

A major uncertainty in the diffusion of autonomous vehicles is the split between ownership and automated mobility services. We calculate total cost of ownership and use (TCOU) to compare four alternatives: private manually driven vehicles, private automated vehicles, automated on-demand exclusive use mobility services (ridesourcing) and automated on-demand pooled mobility services (ridesplitting), for both conventional and electric propulsions. We also included potential usefulness of travel time in the driverless vehicles in the TCOU calculations, thus including some of the non-financial factors in travel decision making. While nearly all current studies are limited to comparing average representative trips or mileage of existing vehicles, we calculate TCOUs for every vehicle in the UK National Travel Survey dataset, considering heterogeneity in mileage patterns, trip purposes, time spent driving, value of time, vehicle age, depreciation and other factors between different vehicles. The results suggest that a near-total transition to automated ride services is highly unlikely, since ownership of (automated or manually driven) vehicles continues to be the least-cost option in most cases. Even in the most pro-mobility service test case, ownership remains more cost-effective for one third of the current vehicle fleet. Regression analysis shows that higher income of the main driver, business use of the vehicle, rural location of the household or being the main household vehicle leads to a higher likelihood that automated vehicle ownership will be lower cost compared to automated mobility services. Within automated on-demand ride services, exclusive use services are cost effective for more cases compared to pooled, shared-use type options, with uncertain consequences for future travel demand.

Keywords

Driverless cars; shared autonomous vehicles; car ownership; ridesharing; travel time costs; ridehailing

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1. Introduction

Ever since Google's demonstration in 2012 of fully automated (i.e. autonomous, driverless or self-driving) cars, these vehicles have attracted intense attention from the media and expectation from members of the public. Nearly all the major vehicle manufacturers now have a fully automated vehicle (FAV) program. As such, the question is no longer about 'if' but 'when' and 'how' these vehicles will cross the boundary between pilot on-road demonstrations to actual use on road by the consumers. Given the disruptions that the FAVs can cause to the status quo, there is increasing research on the potential impacts of automated vehicles on various aspects of the transport system. The impacts studied to date include effects on road safety (Department for Transport 2015a, European Transport Safety Council 2016), on travel behaviour and travel patterns (Wadud et al. 2016, Krueger et al. 2016, Fagnant and Kockelman 2014, Spieser et al. 2014, Yap et al. 2016, Harb et al. 2018), insurance industry (Miller 2015), infrastructure (Transport Systems Catapult 2018, Farah et al. 2017), accessibility (Meyer et al. 2017), location choices (Milakis et al. 2018), energy and carbon (Wadud et al. 2016, Wadud and Anable 2016) and other societal outcomes (Correia et al. 2016).

One crucial uncertainty in all of the impact studies is the future extent and pace of uptake of automated on-demand mobility services (taxis, private hire vehicles or minicabs, e-hailing, ridesourcing, pooled-ridesourcing or ridesplitting) – sometimes together referred to as shared automated vehicles (SAV).[1] Taking the human driver out of the equation to provide fully automated on-demand mobility services would likely substantially reduce the costs of providing these services (Bosch et al. 2018, Burns et al. 2013, Bronwell and Kornhauser 2014) and make them more attractive than vehicle ownership – at least from a financial perspective. Citing primarily grey literature, the media often reports the 'end of car ownership' as imminent, even within the next 10 years (Harris 2017, Rowlatt 2018). It is therefore vital to understand what share of vehicle owners may switch

[1] The definitions of various emerging mobility services such as e-hailing, ridehailing, ridesourcing, ridesplitting, ridesharing, pooled ridesourcing, are still evolving in the literature, and can sometimes be confused with more established services like carsharing or car clubs or carpooling, see Shaheen et al. (2019) and SAE International (2018) for a classification. Different terms are sometimes used to mean the same thing in different parts of the world too (Wadud 2020). In this paper we investigate two specific on-demand 'commercial' mileage-based mobility services: an exclusive-use ride service (similar to ridesourcing or private hire vehicles in the UK, for example UberX or Addison Lee in London) and a shared-use or pooled ride service (similar to ridesplitting, for example UberPool or LyftLine). 'Ride services' or 'mobility services' in this paper refers to a combination of these two services, not the 'Mobility as a Service' (MaaS) operations as seen in cities like Helsinki.

from owning vehicles to using automated mobility services, in order to quantify the impacts of FAVs on transport system and travel patterns, and thus help formulate appropriate policies and strategies.

This research aims to fill this gap by first asking what share of currently privately owned vehicles will become more expensive to operate compared to using automated mobility services or owning a private automated vehicle. We estimate the costs of different types of automated mobility or ride services for conventional and electric powered vehicles and compare that with the total costs of ownership (TCO) of every vehicle in the UK National Travel Survey (Department for Transport, 2017) dataset. As such, this research provides the first comprehensive comparison of FAV ownership with the adoption of automated on-demand ride services, based on a large-scale, nationally representative dataset, and considering the heterogeneity in the travel and cost profile among vehicles. The comparison includes privately-owned manually-driven vehicles (PMDV), privately-owned automated vehicles (PAV), on-demand exclusive-use automated ride services (OEAR, similar to ridesourcing services) and on-demand pooled automated ride services (OPAR, similar to ridesplitting or pooled ridesourcing services), with the automated options further investigated for both conventional fuel and electric propulsion. Building on a method pioneered by Wadud (2017) and Wadud et al. (2016), we also incorporate in the TCO analysis the potential benefits of useful use of time in FAVs, thus including – at least partially – some non-monetary elements of vehicle usage costs and their impacts on the decision-making process. Using these results, the second aim of the research is to identify the socio-economic characteristics of vehicle users that can be associated with the relative attractiveness of FAV ownership and the use of automated ride services, which can be especially useful for transport researchers, planners and policymakers.

The paper is laid out as follows. Section 2 provides a brief introduction to literature in the area, identifies research gaps and explains further the contribution of this paper. Section 3 describes the methods and data used. Section 4 discusses the TCO results, along with sensitivity tests. Section 5 describes the results of a regression analysis to identify the socioeconomic characteristics that affect the attractiveness of automated vehicle ownership and mobility services. Section 6 draws conclusions.

2. Insights from literature

2.1 Costs of ownership and car purchase

An individual's decision to purchase and use a vehicle for personal use depends on a number of factors and there is a large literature on this topic (e.g. Steg 2005, Choo and Mokhtarian 2004). Lane and Potter (2007) group these influencing factors into two categories: situational and psychological. Situational factors can often be measured objectively and include vehicle economics, regulatory environment, vehicle performance and suitability or infrastructure provisions. On the other hand, psychological factors are more difficult to quantify and can include the individual's attitude, lifestyle, personality and self-image. Lane and Banks (2010) found that consumers in the UK identified situational factors (vehicle fuel economy/running costs, vehicle size/practicality and vehicle prices) as the most important factors when purchasing their most recent private car. Similarly, Tran et al. (2013) conclude that financial costs and benefits are still the most important criterion affecting private vehicle purchase decisions in the UK. These studies underline the importance of financial considerations on vehicle purchase and mode choice decisions.

From a car owner's perspective, vehicle economics is best expressed through total cost of ownership (TCO). TCO analysis calculates the costs of owning and using a vehicle over its useful life or during the period of ownership. The key advantage of using a TCO analysis is that it covers not just upfront purchase costs but also recurring ones (fuel, maintenance, tires, vehicle inspection), which provides an accurate picture of the out-of-pocket costs of using privately-owned vehicles. TCO analysis is extensively used in techno-economic studies to compare competing vehicle technologies (e.g. Lipman and Delucchi 2006, Thiel et al. 2010, Contestabile et al. 2011, Palmer et al. 2017). Wadud (2017) also argued that time costs are an important part of the TCO equation, especially in the context of vehicle automation, and included the costs of driving time in his TCO calculations for automated vehicles. Clearly, TCO is not the only factor influencing vehicle technology or transport mode choice, but as mentioned above, it is amongst the most important ones. Since we are also interested in comparing automated vehicle ownership with on-demand automated mobility services, which is a user charge-based system, we use the term Total Cost of Ownership or Use (TCOU) in the rest of the paper.

2.2 Adoption and use of FAVs

There are several strands of literature that attempt to model the effects of automated vehicles on travel decisions, and are therefore relevant to this research. These are described briefly below.

Lavasani et al. (2016) and Trommer et al. (2018) assume automated vehicles will primarily be privately owned and use Rogers' S-shaped technology diffusion/adoption curve (Rogers 1995) to understand the future penetration of FAVs in the vehicle fleet. Talebian and Mishra (2018) follow similar theory of diffusion, but use an agent-based approach on a synthetic population to understand adoption. In addition to the lack of the any data to fit a Rogers curve, a strong limitation of these types of studies is the exclusive focus on ownership – especially in the context of recent growth in the use of Uber, Lyft, Didi and such on-demand, manually driven ride services globally.

The second strand of literature investigates the willingness to pay for various automation functions in privately-owned automated vehicles, using stated preference surveys or choice experiments (Bansal and Kockelman 2016, Daziano et al. 2016). While the results of these studies can be used to understand or simulate the potential penetration of automation in the privately-owned vehicle fleet, they do not investigate the potential adoption of FAVs in the future and are more interested in the factors affecting adoption.

Cools et al. (2016) and Moreno et al. (2018) aim to understand individual intention to own an automated vehicle and/or use on-demand automated ride services. While these studies use online questionnaire surveys, Zmud and Sener (2017) investigate psycho-social constructs more in depth with a focus group study. Choice experiments are also used in understanding individual preferences between automated vehicle ownership and automated on-demand mobility services (e.g. Haboucha et al. 2017, Azgari 2018, Clayton et al. 2018). Some of the choice experiment-based research (e.g. Daziano et al. 2016) investigates automated on-demand ride services only, but generally on a trip-basis, i.e. with no choice between ownership and ride services. Others, e.g. Menon et al. (2018), investigate the effects of socio-demographic and attitudinal factors on the willingness to relinquish an existing (manually-driven) vehicle in favour of the automated mobility services, but do not include the costs of ownership or services, which is an important choice determinant.

A large literature adopting a socio-psychological perspective uses the unified theory of acceptance and use of technology (UTAUT) and/or variants thereof to investigate the acceptance (but not necessarily adoption) of automated vehicles (Merat et al. 2017, Nordhoff et al. 2018, Panagiotopoulos and Dimitrakopoulos 2018, Lavieri et al. 2017). While UTAUT can have an economic component through performance expectancy, these studies primarily focus on socio-psychological factors, such as trust in new technology, and as such are not directly relevant here given our focus on the relative economic attractiveness of ownership and on-demand services.

Another strand of the literature attempts to calculate the future TCOUs for ownership and automated passenger or freight services under plausible future scenarios of automation. For example, Wadud (2017) compares TCOUs of average representative privately owned FAVs with that of average automated taxis and automated freight trucks to suggest that the *commercial* services will benefit the most from automation. Bosch et al. (2018) and Becker et al. (2020) compare per-mile costs of average mobility services undertaken in automated and manually driven vehicles. These studies are important inputs to choice experiments or other adoption models, but stop short of investigating the potential split between ownership and on-demand ride services.

While consumer survey-based academic studies reveal drivers' scepticism about using automated on-demand mobility services (e.g. Haboucha et al. 2017 find that one-fourth of drivers will not use automated ride services even if their cost is zero), some experts suggest that by 2025 car ownership in the UK will fall by more than 50% (KPMG 2018). Other cost-based studies suggest that 95% of the vehicle-miles in the US will be undertaken by automated on-demand mobility service vehicles by 2030 (Arbib and Seba 2017). The main limitation of the cost-based studies, which is the primary focus of this study, is that they typically compare only *average representative* per mile cost of a privately owned manually driven vehicle (PMDV) vs. a future automated on-demand ride service (OEAR or OPAR), often electric powered (e.g. Burns et al. 2013). However, TCOUs of existing vehicles can vary substantially depending on both vehicle and travel characteristics. For example, even for two otherwise identical cars, the older or more heavily used one will have a lower annual depreciation cost than the newer or lightly used one. Studies on value of travel time suggest that the costs of driving time can also vary substantially among people, depending on factors such as income and trip purpose. As such, an average representative TCOU in the above studies fails to acknowledge the importance of heterogeneity in the actual travel patterns of people, as well as the associated travel costs and runs the risk of miscalculating the extent of FAV uptake, particularly with regard to the relative share between ownership and mobility services. Therefore, this paper goes beyond those previous studies by incorporating the heterogeneity of TCOUs in understanding the share between ownership and mobility services in a FAV era.

3. Methods and data

3.1 Components of TCOU

TCOU for vehicle ownership is the sum of all private costs related to purchasing and using a car over the ownership period. It can also be calculated on an annual basis or average-years-of-ownership basis. Traditional TCOU analysis includes the costs of vehicle purchase (such as annual depreciation), fuel (or electricity), insurance, maintenance and repair, engine oil, cleaning and servicing, tire replacement, safety and emissions inspection fee (MOT in the UK), parking, tolls or similar out-of-pocket costs (Lipman and Delucchi 2016). The social costs of driving (e.g. emissions and noise) are generally not included in TCOU analysis, since they are mostly borne by others and thus often not considered (or, at best, qualitatively considered) in individual vehicle purchase decisions. For on-demand ride services, TCOU is simply the sum of costs incurred by the user if the existing car trips over the ownership period are instead undertaken by these ride services.

One of the largest non-financial costs of owning and using a car is the time spent in driving since this requires constant nearly-full attention from the driver. Fully automated vehicles offer substantial savings in these time costs as they can relieve the driver of the driving duties, so that driving time can be spent on other desirable activities. In the UK, currently a driver spends on average 274 hours a year driving, with the additional driving time related productivity benefits of FAVs estimated at £20 Billion (KPMG 2015). Wadud and Huda (2018) also investigated how people can engage in various useful activities while in FAVs and how that is directly related to their intention to use these vehicles. Given the importance of time-costs, Wadud (2017) included them in his TCOU analysis, and we also include the costs of time in TCOU calculations, along with the other items mentioned earlier.

The TCOU cost elements included in this study are depreciation (automated and manual), cost of capital, insurance, road tax, MOT tests, vehicle breakdown cover, fuel, replacement tyres, service labour and parts, and parking, road tolls as well as unproductive travel time, all calculated on an annual basis. For mobility services, overhead (including cleaning, licenses) and profit margin are added, while parking is not included, assuming the automated mobility service vehicles will not be requiring any paid parking. TCOUs are calculated at the vehicle level, since our objective is to determine whether it would be cheaper for the driver to replace the existing manually driven vehicle (PMDV) by a privately owned automated vehicle (PAV) or by on-demand automated ride services (OEAR or OPAR).

3.2 Vehicle and travel data from NTS

The National Travel Survey (NTS, Department for Transport, 2017) is a continuous survey designed to assess the travel behaviour of *English* residents within Great Britain, using a representative sample. The analysis in this paper is based on data for 2015, i.e. the most recent year available at the time of the analysis. A key feature of the NTS is that all household members complete a seven-day travel diary, which provides a more representative picture of travel behaviour at the household and individual level than what is achieved by surveys with one- or two-day diaries. Our analysis sample consists of 7,360 vehicles (four-wheel cars and land rover/jeeps), i.e. all vehicles belonging to households with complete travel diary information, except 47 vehicles with missing data.

The NTS gathers information on households, individuals, trips (defined by purpose), stages (sub-sections of trips, defined by travel mode), as well as household vehicles. The vehicle dataset contains details about vehicle characteristics (e.g. vehicle make, model, age, fuel type, carbon emissions, engine size) as well as vehicle use. Every vehicle in the dataset can also be linked to the characteristics of the household to which it belongs (e.g. socio-demographics, number of vehicles in the household and type of area of residence) as well as to the details of the individuals reported as the 'main driver'. The seven-day travel diaries record the vehicle which was used for an individual's car travel, and this information can be used to estimate the total time a vehicle is used, average occupancy and purpose of the trip. Self-reported annual mileage broken down by different trip purposes is also available for each vehicle.

The following variables have been used for the TCOU calculations: vehicle mileage; estimated fuel consumption (multiplied by fuel price); total duration of use during the diary week (extrapolated to annual use); and share of time for different travel purposes (business, commute, other).[2] To derive a unique income value for each vehicle, we averaged the individual income of the different household drivers, weighting by their driving time over the week in that vehicle. Vehicle make, model, and age is linked to the depreciation table (see section 3.4) to calculate annual depreciation costs, while driver age and vehicle types are used to calculate insurance costs. The socio-economic characteristics and residential location of main driver, the number of children and adults in the household and the number of cars in the household are used as predictors in the regression models that we estimate after the TCOU calculations (see sections 3.5 and 5).

3.3 Time costs

One of the main anticipated advantages of fully automated vehicles is that they would allow drivers to engage in useful activities while on board, as driving would no longer require user attention (Wadud and Huda 2018). This has the potential to reduce the costs of travel time, or the Value of Travel Time Savings (VTTS). In order to calculate the time costs, we follow Wadud's (2017) approach. In short, we start with UK Department for Transport's (2015b) Webtag guidance for different VTTS for three trip types in manually-driven vehicles (business £24.78, commute £7.42, other £6.59) and assume that these values are applicable for the mean income of the main drivers in the NTS sample. We then use an income elasticity of VTTS of 0.7 (Wardman 2004) in conjunction with the time-weighted income of the main driver and passengers to generate vehicle- and trip purpose-specific VTTS for every vehicle. This is combined with total hours of driving for each of the three trip purposes in every vehicle to obtain the annual costs of time associated with each vehicle. As such, the time cost differs by income, hours driven and trip purposes.

Following our earlier discussion, and literature on lower VTTS of car and train passengers compared to car drivers, several authors (Wadud et al. 2016, Wadud 2017, Fagnant and Kockelman 2015) have argued that VTTS will be lower in fully-automated or on-demand mobility services vehicles. Lending credibility to this argument, Steck et al. (2018) used a choice experiment to report a reduction of VTTS of 31% in FAVs for commute trips in Germany. For this work, we use a reduction of 40% in PAVs

[2] Purpose of trips: business = travel for employer's business or own business; commute = travel to/from work/school; other = rest

as per Ian Wallis Associate's (2014) review of car driver and passenger VTTS estimates, which was also adopted by Wadud (2017) and Wadud et al. (2016).[3]

It is well known that a vehicle provides an 'own space', which is valued highly by the drivers (Fraine et al., 2007; Mattioli, 2014; Wells and Xenias, 2015). Different users will use their time in FAVs in different ways (Wadud and Huda 2018), and ownership will allow each owner to configure the vehicle interior according to their needs, and thus to maximize his/her utilization of time inside the vehicle. As such, time in an owned vehicle is likely to be used in more useful ways as compared to an on-demand ride services vehicle. This hypothesis is supported by Steck et al. (2018), who show that the reduction in VTTS for commuters in an owned vehicle is three times that in a mobility services vehicle. Therefore, we assume conservatively that the reduction in VTTS in an OEAR is half that in a PAV. Similarly, VTTS reduction in an OPAR vehicle is assumed to be half that of an OEAR vehicle, given that users may not be able to utilize the 'shared' space as effectively in the presence of other passengers, as was observed in the GATEway project in the UK (GATEway 2018).

3.4 Other costs

Many of the out-of-pocket costs are from Wadud (2017), which is based on AA (2015), with some important modifications. One key innovation in this work is the use of vehicle age, make and model-specific depreciation rates to calculate annual capital cost. The age-specific marginal annual depreciation rate is important, since at any point in time the vehicle stock contains vehicles of different age, which results in quite different annual depreciation costs because the marginal annual depreciation rate is non-linear over age. Depreciation also varies by vehicle make (and model), so the differences in depreciation based on vehicle make are also considered in this study. Fig. 1 shows the distribution of annual depreciation costs across the 7,360 vehicles in the NTS dataset. At the high end of this distribution are luxury vehicles which have been bought new during the year of the survey, resulting in very high depreciation in the first year, while at the low end are older vehicles which have possibly reached the end of their working life. The median annual capital costs is only £766, and nearly three-fourths of the vehicles have an annual capital cost under £1,414, revealing the low annual depreciation costs of the existing vehicle stock. The depreciation costs for the average new mid-range petrol car in AA (2015) is £2,611, indicating the importance of using actual vehicle age, make, model and depreciation for each vehicle separately in TCOU calculations.

[3] Building on previous work (Jara Díaz & Guevara, 2003), a very recent paper by Jara-Díaz (2020) decomposes VTTS into a value of liberated time and a value assigned to the conditions of travel. This framework can be useful in understanding time use and its valuation in automated vehicles further. Given the unavailability of these decomposed values for the UK or for AVs at the time of writing, we use the more established VTTS.

Fig. 1 Distribution of annual depreciation costs for existing manually driven vehicles (PMDVs) in the NTS dataset, in ascending order

Following a literature review, Wadud (2017) assumed £9,400 as the additional cost of automation technology in new cars in the assumed first year on the market (2020). For a substantial penetration of automation in the vehicle fleet, a lower additional costs – £5,000 – appears more reasonable, which is used in the baseline calculations here. In the UK, it is very common for mobility-service vehicles (private hire vehicles, minicabs, e-hailing) to be bought second-hand in order to avoid the high depreciation of newer vehicles. As such we assume the OEAR and OPAR vehicles are bought second hand too, with lower capital and depreciation costs compared to new automated vehicles.[4]

Insurance costs are also expected to fall dramatically when automated vehicles become widespread (Light 2012). While Wadud (2017) used a conservative reduction of 20% in insurance premium for early FAVs, the reduction may be even larger due to the volume effect (whereby when many vehicles are automated, every vehicle benefits of a larger insurance premium reduction). Nearly 70% of the vehicle's insurance premium is for the human driver and 30% for the vehicle (Miller 2015). The age of the driver is also an important parameter in determining insurance premiums, and the wide difference in the age-wise insurance premiums, £713 between the highest and lowest groups, reflects this (Association of British Insurers 2017). We assume that all FAVs will be at least as safe as the safest driver group, and use the premium of that group as benchmark for automated vehicles (£260). 70% of this remains constant for all vehicles – reflecting no age effects of the driver, while the rest varies according to the price of the vehicle.[5] For automated on-demand mobility service vehicles, insurance costs are reduced by one-third from Wadud's (2017) taxi insurance costs to reflect the commercial nature of the liabilities, which tend to be higher than private liabilities.

[4] Although maintenance costs can high for second-hand vehicles, depreciation costs of new vehicles are significantly higher, making purchase of pre-owned vehicles more attractive. Access to credit to purchase new vehicles can also be limited for the taxi drivers.

[5] The relationship was derived using AA (2016) insurance costs and price of new vehicles.

Current fuel costs are derived directly from fuel prices, annual mileage, CO_2 rating of vehicles and fuel type (on the basis of which we calculate fuel efficiency) and a factor to reflect real life fuel efficiency, which varies by fuel type. For EVs we use electricity costs of £0.03/mile.[6] We also assume a 5% improvement in fuel efficiency in FAVs to reflect potential built-in eco-driving algorithms in these vehicles as per Wadud (2017). Maintenance costs are mileage dependant, too (based on Leanse 2016).

The current costs for on-demand mobility services are modified from Wadud's (2017) taxi costs and approximately match with current prices for non-automated vehicles.[7] For OEARs, driver costs are removed and per-mile costs recalculated on the basis of annual mileage of 40,000 miles, a load factor of 60% (i.e. 60% of the total mileage is paid for, the rest is deadheading/empty running).[8] Also included is a 15% profit margin over the financial costs of automated mobility vehicles. For OPAR services, a mileage penalty of 5% included for additional pick-up and drop-offs, but price to the consumer is reduced by 25%.[9] Table 1 presents the sources or assumptions for the various cost components. Table 2 presents the cost estimates for the different automated mobility services. These cost estimates are larger than some of the US grey literature (e.g. for OEAR electric, $0.16/passenger-mile (Arbib and Seba 2017), OEAR conventional $0.41/trip mile (Burns et al. 2013)), but are very similar to other academic works such as Bosch et al. (2018) for Switzerland.

Table 1. Input data and their sources TCOU calculation for PMDV, PAV, OEAR and OPAR services for baseline calculations

	PMDV*	PAV*	OEAR#	OPAR#
Vehicle purchase costs	Based on make, model (NTS)	PMDV costs + £5,000 auto.	Pre-used, £15,000 + £3,000 auto.	Pre-used, £15,000 + £3000 auto.
Annual depreciation costs	Based on vehicle depreciation category and age (NTS), using confidential data[10]	Similar to PMDV, but base price considers automation	4 year depreciation	4 year depreciation
Fuel costs	Based on vehicle CO_2 rating, fuel	5% gain in fuel economy over PMDV	Based on mileage (NTS) and Wadud	Based on mileage (NTS) and Wadud

[6] https://www.sust-it.net/miles-per-gallon-mpg-fuel-efficient-cars.php?fuel=electric
[7] http://uberestimate.com/prices/
[8] In the UK, taxis and minicabs runs 25,000 to 35,000 miles a year (Insure Taxi 2016). US data shows current ratio of paid mileage to total mileage in ridesourcing services is around 60% (Henao and Marshall 2018, Clewlow and Mishra 2017). While empty mileage is likely to vary by density of population, we have found no suitable data to estimate this.
[9] In London, this ranges between 15% and 25% (https://www.uber.com/en-GB/blog/london/uberpool-whats-new/), we assume higher use in an automated mobility environment will allow a larger reduction, hence 25%.
[10] We had access to a confidential age-specific marginal annual depreciation rate table for four vehicle groups: high, average, moderate and low; and a separate publicly available table with vehicle makes and models that fall within each of these groups (http://www.wisercarbuyer.com/depreciation-by-model.html, accessed July 2017) and vehicle prices (http://www.carpages.co.uk/car-insurance-groups/, accessed July 2017).

	type, mileage (NTS) & retail fuel price[11]		(2017) taxi fuel costs	(2017) taxi fuel costs
Maintenance costs	Based on mileage (NTS) and Leanse (2016) per-mile costs	Based on mileage (NTS) and Leanse (2016) per-mile costs	Based on mileage (NTS) and Leanse (2016) per-mile costs	Based on mileage (NTS) and Leanse (2016) per-mile costs
Insurance costs	Based on driver age & vehicle type (NTS)	= PMDV safest driver costs + varies with vehicle price[12]	assumed 33% reduction over Wadud (2017) taxi insurance costs	assumed 33% reduction over Wadud (2017) taxi insurance costs
Parking, toll, VED, breakdown cover etc.	Based on AA (2016)	Based on AA (2016)	Based on Wadud (2017) taxi	Based on Wadud (2017) taxi
Overheads, incl. cleaning, licensing etc.	n.a.	n.a.	Based on Wadud (2017) taxi costs	Based on Wadud (2017) taxi costs
Vehicle mileage	NTS	NTS	40,000	same as OEAR + 5% penalty
Hours travelled	NTS	NTS	NTS	NTS + 5% penalty (Wadud 2017)
Empty running	n.a.	n.a.	40% (Henao and Marshall 2018)	40% (Henao and Marshall 2018)
Service prices to users	n.a.	n.a.	Costs + 15% profit margin	25% reduction on OEAR
Value of travel time saved (VTTS)	Income and purpose specific	40% reduction from PMDV (Wadud 2017)	20% reduction from PMDV, assumed	10% reduction from PMDV, assumed

* PMDV and PAV values are unique for every vehicle in the NTS dataset

OEAR and OPAR values are representative costs for the automated ride services

Table 2. User costs per mile for PMDV, PAV, OEAR and OPAR services

	PMDV*	PAV*	PAV electric*	OEAR conv. #	OPAR conv. #	OEAR electric#	OPAR electric#
User monetary costs (£/m)	0.54	0.62	0.60	0.69	0.52	0.57	0.43
User time costs (£/m)	0.37	-40%	-40%	-20%	-10%	-20%	-10%

* PMDV and PAV values are mean over the whole sample of the vehicles in the NTS dataset

OEAR and OPAR values are representative costs for the mobility services; load factor (fare mile/total mile) is included in these estimates

3.5 Association with socioeconomic characteristics

[11] For some missing values of CO2 rating in NTS dataset, we imputed values as follows: we used NTS data to estimate an OLS model predicting vehicle CO2 rating with four predictors (type of vehicle, engine size, type of fuel, and vehicle age), selected based on the demonstrated association with CO2 emissions. We then imputed missing values based on this regression model (Adjusted R^2 = 0.76).The regression equation is as follows: CO2 rating = 80.37 + 3.18 Vehicle Age – 34.04 Dummy-Diesel – 144.26 Dummy-Other + 15.66 DEng-0.7-1.0 + 31.70 DEng 1.0-1.3 + 41.54 Deng 1.3-1.4 + 53.09 DEng 1.4-1.5 + 61.60 DEng 1.5-1.8 + 82.0 DEng 1.8-2.0 + 110.95 DEng 2.0-2.5 + 136.6 DEng 2.5-3.0 + 177.24 DEng 3.0+, where "DEng" identifies dummies for engine size.

[12] PAV insurance cost = £260 * 0.7 + 0.008 (price of new vehicle + £5000)

Once the annual TCOUs (sum of monetary and time costs) for the different alternatives are calculated for the specific travel pattern of each vehicle in the NTS dataset (following the methods described above), it is possible to compare these options for each vehicle and identify the least-cost alternative for the travel undertaken by that vehicle. This allows the calculation of the share of different alternatives – PMDV, PAV, OEAR and OPAR – that would be the least-cost options for the whole vehicle fleet in NTS.

In addition to the aggregate presentation of the share of different alternatives in an automated vehicle future, we are also interested in understanding the socio-economic characteristics of the main drivers and the households that can affect the likelihood of one of the options to become the least cost-option to replace the travel of the vehicle. Given that the dependent variables are categorical, we can run a multinominal logit (MNL) or multinomial probit (MNP) regression to model the probability that one of the alternatives would be the least-cost alternative. [13] Note that our units of observation are not people, rather vehicles, so MNL or MNP is used as a regression tool, rather than a utility-maximizing economic choice modelling tool. As such, we do not have any alternative specific variables in the model and the explanatory variables are primarily characteristics of the main driver, household or the vehicle (e.g. whether the vehicle is the first or second car of the household). MNP offers two significant advantages over MNL in this context. Firstly, it allows for correlation of errors across the categorical outcome unlike MNL, and secondly, the error distribution is symmetric in MNP, which is useful since we are discussing categories that have been initially calculated as least-cost options.[14] As such we employ MNP in this study.

4. TCOU Results

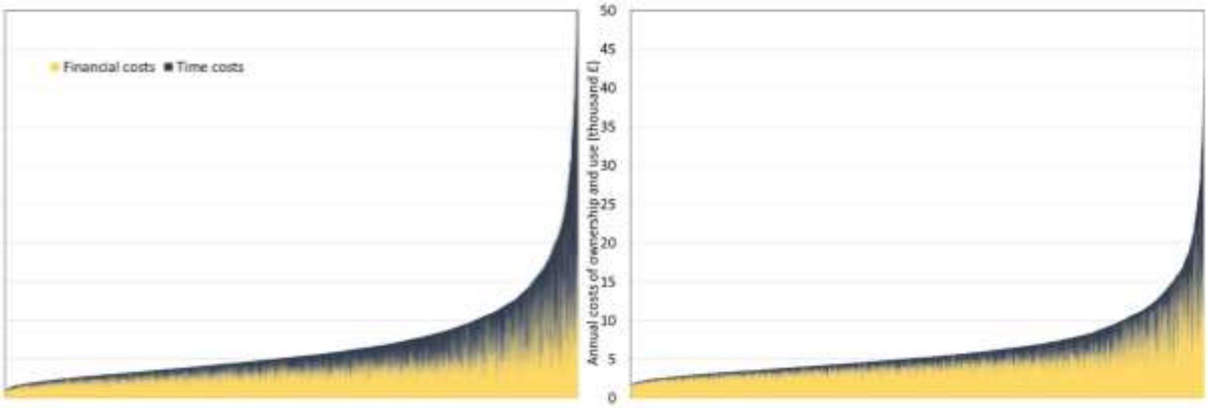
4.1 Distribution of TCOUs

Fig. 2 (a) presents the breakdown and distribution of TCOUs of the current manually-driven vehicle fleet in the NTS dataset. These annual total costs are sorted in ascending order, and the wide range is immediately visible. At the low end of total costs are generally older vehicles with minimal depreciation costs, which are used very little, by drivers with low income and a low value of time. At the higher end, the vehicles are generally more expensive and newer (hence higher depreciation costs), are used substantially more than average by higher income people, so that the time costs are

[13] Given MNL and MNP models are fairly standard in literature now, we do not include the mathematical formulation here. Readers are suggested to consult any transport modelling, econometric modelling or choice modelling text book (e.g. Ortuzar and Willumsen 2011). The key difference is the distribution of errors, for MNL it is Extreme Value Type I, for MNP it is multivariate Normal (Ortuzar and Willumsen 2011).

[14] Although we do not use a choice modelling framework here, our underlying categorical variables represent 'least-cost' options, hinting at disutility minimization, instead of utility maximization. As Misra (2005) shows, the results of both modelling philosophy results in the same estimates for MNP, but not for MNL.

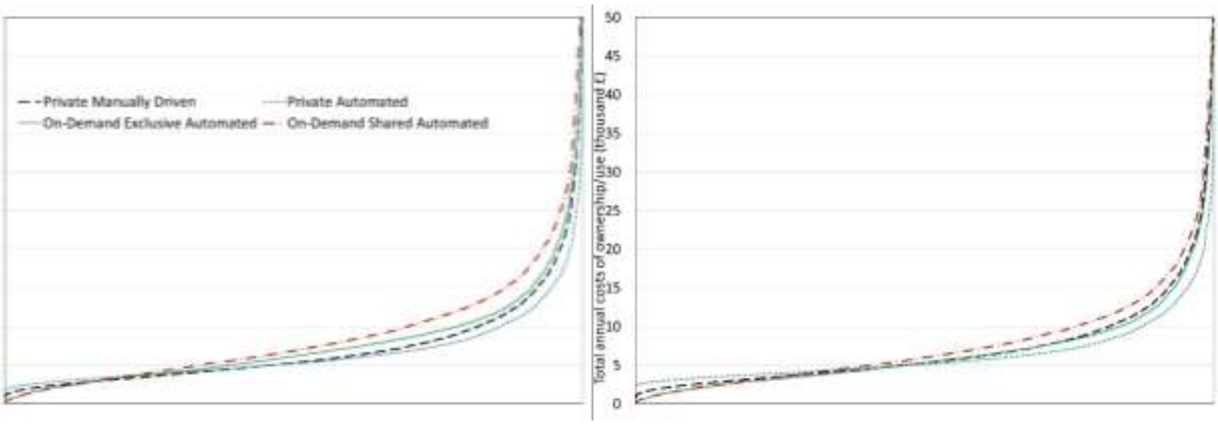
also high. Fig. 2 (a) also shows that there is a wide variation between the time costs (darker shade) and financial costs (lighter shade) of each vehicle, and shows the importance of considering heterogeneity in individual costs instead of using average representative ones, as in most research to date (Wadud 2017, Bosch et al. 2018).



(a) PMDV (b) PAV

Fig. 2 Distribution of annual costs of ownership in ascending order for (a) privately owned manually driven vehicles (PMDVs) and (b) privately owned automated vehicles (PAVs)

Fig. 2 (b) presents the breakdown and distribution of total costs for privately-owned automated vehicles (PAVs), once again, in ascending order. While the financial costs (lighter shade) are higher due to higher capital costs, time costs (darker shade) are now much smaller in comparison, because of useful use of time. Fig. 3 (a) compares the distribution of total annual costs for PMDV, PAV, OEAR and OPAR – all using conventional fuels – without the breakdowns of Fig. 2. Fig. 3 (b) presents the distribution of costs for the same ownership and mobility options, but the three automated options are electricity powered.



(a) (b)

Fig. 3 Distribution of TCOUs for the four ownership and on demand mobility services in ascending order (a) all conventionally fuelled (b) all but private manually driven are electricity powered

4.2 Least cost alternatives

While the distributions in Figs. 2 and 3 reveal the wide range of costs associated to the vehicles in the NTS dataset, they cannot be directly used to identify the least-cost alternative for each vehicle. This is because each series is plotted in an ascending order, which alters the relative positions of individual vehicles. Therefore, we identify the least-cost option for maintaining the travel by each of the vehicles in the NTS dataset. Figs. 4 (a) and (b) present the weighted (household weights from NTS) share of the alternatives for which they are the least-cost options to the user. As before, (a) presents conventionally fuelled automated vehicles, while (b) presents an automated-electric future – both compared against the currently owned vehicles – all manually-driven and conventionally-fuelled (except for the few existing alternative fuelled ones in the dataset). Fig. 4(a) shows that for nearly one-quarter (24.8%) of the vehicle fleet, a privately-owned, manually-driven vehicle (PMDV) will still be the least-cost option even when automated vehicles or automated on-demand ride services are available. For 42.4% of the fleet, privately-owned automated vehicles (PAV) will be the least cost option. On-demand automated ride services are cost competitive for the trips undertaken by only one-third (32.8%) of the current vehicle fleet. More specifically, on-demand exclusive use (OEAR) and on-demand pooled/shared-use vehicles (OPAR) would be the least-cost option for 16.5% and 16.3% of cases. Fig. 4b shows that the on-demand electric mobility services become the cheapest option for 45.6% cases, with primarily conventionally-fuelled PMDVs losing out their share. Lower financial costs per mile resulting from higher utilization of on-demand vehicles make the higher capital costs worthwhile for electric vehicles and makes them less expensive as compared to conventionally-fuelled PMDVs.

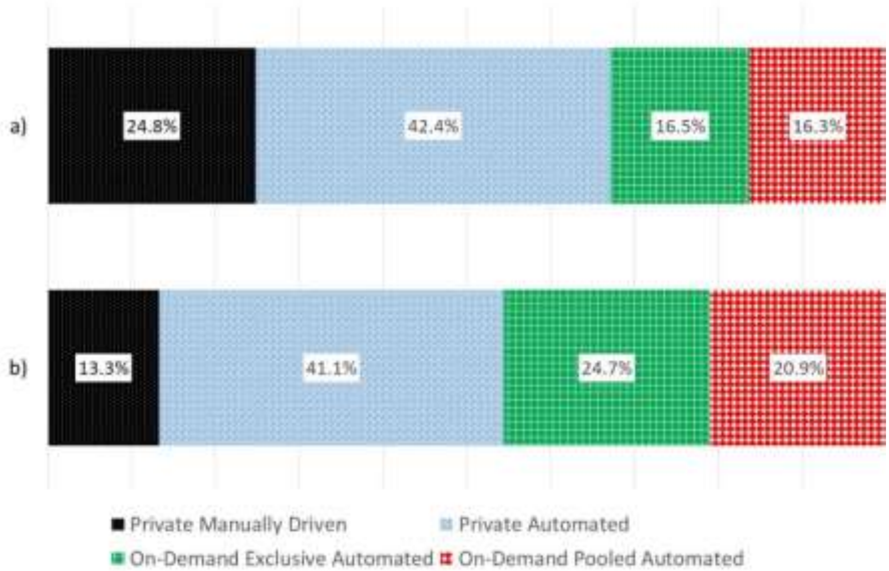


Fig. 4 Weighted share of different ownership and mobility service options with the least cost (a) all conventionally fuelled (b) all but private manually driven vehicles are electric powered

4.3 Sensitivity analysis

Given the uncertainties in some of the input parameters, we conduct a series of sensitivity assessments to understand the effects of alternate input values or assumptions on the results in Fig. 4. Table 3 presents the sensitivity of the weighted shares of PMDVs, PAVs, OEAR services and OPAR services for which they are the least-cost options. It is important to note that the sensitivity tests presented here aim to explore the sensitivity of the results to the chosen parameters, not to quantify the overall uncertainty in the results.

4.3.1 Effects of value of travel time

Wadud (2017) reported that VTTS has a substantial effect on the TCOU of privately-owned automated vehicles (PAVs). Our first sensitivity analysis assumes a more useful use of time in all automated vehicles compared to our base case, but the relative usefulness between owned and mobility services remains the same. The related parameters are: 60% reduction in VTTS for PAVs, 30% for OEAR services and 15% for OPAR services (a 50% change compared to the reductions of 40%, 20% and 10% respectively in the base case). Since the PAVs stand to gain the most through improved usefulness of time (i.e. lower VTTS), they become the least-cost alternative for slightly more than half (51.7%) of the sample for conventionally-fuelled vehicles (Table 3, time use+), which is a substantial increase (9.3%) over the baseline scenario. This increase comes from the reduced shares for PMDVs (24.8% to 17.1%) and, to a lesser extent, OPAR services (16.3% to 14.4%), while OEAR services do not show much change (16.5% to 16.7%). A similar trend is observed for automated electric vehicles, where the ownership option becomes the least-cost option for 47% of the cases, compared to 41.1% in the baseline scenario (Table 3, time use+). The relative usefulness

Table 3. Sensitivity of the weighted share of least cost alternatives with respect to various inputs

	Conventionally fuelled				Electric powered			
	PMDV	PAV	OEAR	OPAR	PMDV	PAV	OEAR	OPAR
Baseline	24.8%	42.4%	16.5%	16.3%	13.3%	41.1%	24.7%	20.9%
Time use +	17.1%	51.7%	16.7%	14.4%	9.7%	47.0%	24.9%	18.3%
Utilization +	16.8%	36.8%	23.5%	22.9%	3.9%	29.1%	39.9%	27.2%
Surge +	26.9%	44.8%	14.8%	13.4%	16.2%	44.1%	22.5%	17.3%
Automation cost +	49.0%	18.7%	16.2%	16.1%	30.9%	23.5%	24.4%	21.3%
Own convenience +	32.9%	45.2%	11.6%	10.3%	23.8%	45.4%	16.9%	13.9%

of time between PAV, OEAR and OPAR services is not further investigated here, but can still be important. Notably, ownership would be even more attractive than our estimates if we had used Steck et. al's (2018) finding that travel time in PAVs could be three times more useful than that inside the on-demand vehicles.

4.3.2 Effects of capital costs

As mentioned earlier, the price of FAVs is a major uncertainty in the TCO calculations. We round up Wadud's (2017) £9,400 to use £10,000 as additional capital costs of automation for a sensitivity test. Capital costs have a large effect on the split between PMDVs, PAVs, OEAR services and OPAR services, with manually-driven vehicles becoming substantially more attractive than the automated ones – whether owned or used for ride services. As Table 3 (automation cost+) shows, PMDVs become the least-cost option for nearly half (49%) of the cases if automation costs for conventionally-fuelled vehicles are higher. This is a large change from our baseline case, where PMDVs were the least-cost option for only one-fourths (24.8%) of the cases.[15] Also, compared to electric automated vehicles, conventionally fuelled PMDVs become substantially more attractive (from 13.3% to 30.9%) if automation costs go up.

Note that the least-cost share of automated on-demand services (OEAR and OPAR together) are quite insensitive to higher costs of automation (32.8% to 32.3% and 45.6% to 45.7% in Table 3). This is a result of the relatively higher utilization of these vehicles cushioning the effects of an increase in automation costs.

4.3.3 Effects of utilization of on-demand vehicles

The base-case costs of on-demand automated ride services is based on an average 40,000 miles per FAV. Frazolli et al. (2014) found that, in a hypothetical scenario, Singapore's current car travel could be served by a fleet constituted exclusively of on-demand vehicles, one-third the size of the current vehicle stock – which means that each vehicle is driven at least three times the average mileage of the privately-owned vehicles. For the UK, this translates to around 24,000 miles a year of paid-miles, and 40,000 miles a year of total mileage at a 60% load factor. There are, however, suggestions that the FAV-based ride service vehicles will be used more intensively (e.g. Arbib and Seba 2017). International Transport Forum (2015) suggests up to 90% of the owned vehicles can be removed (65% in peak hours) with concomitant increases in the mileage of mobility services vehicles, but has

[15] We note that within PMDVs, there are various ownership models possible, especially leasing is becoming popular. However, NTS does not collect information on whether the vehicles are owned or leased or bought through company car schemes; also leasing is more common for new vehicles, which is only a small proportion of the vehicle stock. As such we take depreciation and costs of capital to capture either ownership or leasing costs. However, the various ownership/leasing schemes and their effects is an interesting area for future work.

overly optimistic and possibly unrealistic assumptions such as a 30 minute wait time and shared-rides only[16]. As such, for the sensitivity test we use an average annual mileage of 60,000 miles per ride service vehicle (again, 50% more than the base case). We adjust the depreciation as well since the vehicles are used more intensively in these scenarios and will depreciate quicker than before.

Utilization of on-demand vehicles appears to have a substantial effect on the attractiveness of different alternatives. As Table 3 (utilization+) shows, automated on-demand services become the least-cost option for 46.4% of cases if the on-demand vehicles are utilized 60,000 miles a year, compared to 32.8% of cases for the base case. For electric options, automated mobility services become attractive for 66.1% of cases compared to 45.6% for the base case (Table 3, utilization+). Clearly both ownership options become relatively less attractive as per-mile financial costs of on-demand mobility services fall due to higher utilization.

4.3.4 Effects of surge pricing

Our baseline cost analysis hinges upon plausible capital and running (variable) costs of FAVs, adopting the same supply-side approach followed by all similar studies (e.g. Wadud 2017, Bosch et al. 2018). While such estimates work well with owned vehicles, for mobility services demand is an important parameter in setting the market prices of these services. It is likely that the automated ride service providers will continue to utilize the peak pricing approach (e.g. surge pricing by Uber or Prime Time pricing by Lyft) to match demand with supply in the future. The peak pricing will likely affect the peak-hour commute trips more than other trips. While we did not include any peak pricing in the baseline case, we assume a 100% increase in consumer prices for automated mobility services (both exclusive use and ride share) for 50% of the commute miles. This is also equivalent to a 50% rise for all the commute miles in our modelling approach. Other trip types remain unaffected.

The effects of these modest surge prices on the attractiveness of the four options is not large. Since on-demand services become more expensive due to surge pricing, collectively they lose 4.6% market share (from 32.8% to 28.2%, Table 3, surge+) to ownership alternatives for conventionally-fuelled vehicles, and 5.8% for electric vehicles.

4.3.5 Effects of convenience of ownership

The services provided by an on-demand exclusive or shared-use AV (OEAR or OPAR) and an owned AV (PAV) are not exactly the same, even after discounting the wait time, time use and sharing aspects. For example, the overnight storage function of owned cars (e.g. keeping the child's scooter

[16] Note that this does not necessarily result in a 10-fold increase in mileage of remaining vehicles, since these are shared/pooled-ride vehicles.

or the golf bag in the boot) can be useful to many users.[17] Similarly, the convenience of having a child-seat always fitted in the personal car or having the phone or music system automatically connected to the car (e.g. Bull, 2004) may be attractive to vehicle owners. The peace of mind resulting from having the car immediately and reliably available without any delay can also be valuable to some users. All of these suggest the possibility of a willingness to pay an additional amount for owning a vehicle, which has not been included in the TCOU calculations above. While it is not the objective of this research to estimate these other perceived benefits of vehicle ownership, we run a scenario using £500/year as additional inconvenience cost for automated mobility services.[18,19] As can be expected, on-demand ride services (OEAR and OPAR) become substantially less attractive compared to the two ownership alternatives. For example, electric alternative mobility services become least cost for 30.8% of cases, compared to 45.6% in our baseline scenario (Table 3, own convenience +).

4.4 Discussion on TCOU and least-cost alternatives

Some of the impact or uptake studies compare automated, electric and shared on-demand services with the present-day ownership of conventionally-fuelled vehicles, and optimistically suggest near-total dominance of automated on-demand mobility services in future due to their cost advantages (Arbib and Seba 2017, International Transport Forum 2015). Simulation studies also use future scenarios of 100% automated mobility services (Bronwell and Kornhauser 2014, Fagnant and Kockelman 2014) while the concept of zero-ownership has certainly gained traction in the media too (Harris 2017, Rowlatt 2018). A separate test of our model using only financial costs with PMDVs and on-demand automated, electric mobility services (OPAR-electric) with high utilization (not reported in Fig. 4) indeed supports this narrative, with a very high share (77%) of ride services. However, this simple narrative does not hold if we consider the time use and ownership aspects of FAVs, as we have done in this study. For example, even in an electric-automated vehicle future, nearly 41.1% of the current vehicle owners still find ownership of FAVs to be the least-cost option (Fig. 4b). In this case, the additional savings through useful use of time for an ownership model still outweighs the

[17] https://www.independent.co.uk/life-style/cars-weird-strange-things-kept-inside-driving-hoarding-possessions-survey-a8167426.html

[18] In our vehicle sample there are 217 vehicles for which owning a PMDV is currently more expensive compared to using a human-driven on-demand vehicles (minicab/ridehailing), which are quite expensive. The average difference in annual monetary costs between PMDVs and minicabs for these 217 vehicles is £2,516, which possibly reflects the very high end of the willingness to pay for the *convenience* of owning a car or the cost of inconvenience of minicabs. As such we use £500/year as the additional inconvenience of using on-demand services compared to ownership. Possibly the convenience of ownership will also vary between vehicles depending on income, attitudes to driving and other socio-economic factors of the users.

[19] We are aware of ongoing work on hedonic approach to value the convenience of owning a car at the University of California, Davis by Lew Fulton and colleagues. Wadud and Chintakayala (2020) are also attempting to model the value of convenience of ownership using choice experiments.

additional costs of automation and electrification. The relative usefulness of time in PMDV, PAV, OEAR and OPAR services therefore has an important role in determining the relative shares of these alternatives, and it is important that future studies on uptake and impact take this into account.

While we have used current fuel prices and electricity costs to calculate the TCOU, the costs of electricity may have to increase in an electric vehicle future (automated or not), especially since the reduction in tax revenues from petroleum fuel sales will need to be balanced. While the effects of such responses from policymakers is not the focus of this work, an increase in the per-mile running costs will favour ownership over on-demand automated mobility services.

Although the results were not very sensitive to modest surge pricing, dynamic pricing could have broader effects than can be captured by TCOU analysis. For example, Uber was heavily criticized for its surge pricing strategy during the 2017 terrorist attacks and tube strikes in London, when surge prices went as high as 400%.[20] Anecdotal evidence from the UK also shows that prices go up during inclement weather or large events. Both of these and similar experiences will affect the cost reliability of OEAR or OPAR services, with potential longer-term impacts on the choice between ownership and mobility services that need further investigation.

Utilization of on-demand vehicles has a large effect on the relative cost-attractiveness of the different modes and the resulting shares of uptake. However, utilization has other knock-on effects. For example, realizing a higher average mileage per on-demand vehicle will necessitate a smaller size of on-demand fleet. This will in turn affect waiting time for users, and likely increase service prices at peak hours, both of which will reduce the attractiveness of on-demand services for users. As such, the very high mileage assumed in some studies (e.g. Arbib and Seba 2017), needs to be investigated further in the context of demand-supply interaction.[21]

Many of the optimistic predictions for shared or pooled ride services assume single-person trips, which is not the case in reality. While most car trips in England are single-person, nearly 29% are not. Our use of average occupancy per vehicle and reduced usefulness of time in OPAR services reveals that the relative costs of OPAR services can be higher than those of OEAR services. However, this analysis possibly should be extended in future by incorporating occupancy of every trip of every vehicle to generate individual trip-based TCOUs for mobility services, since users may choose shared services for single-person trips and exclusive use services for multi-person ones.

[20] https://www.standard.co.uk/news/transport/uber-slammed-for-ripping-off-londoners-by-quadrupling-fares-amid-tube-strike-chaos-a3435891.html

[21] A counter example could be the very high utilization of taxicabs in New York City (around 70,000 miles/year). However, the taxi number in New York is artificially capped, creating larger utilization per car.

The least cost options in this analysis are calculated on the basis of the same number of trips, travel distances and journey purposes for all four alternatives – as in the NTS dataset. In practice, there could be secondary effects on these due to cost changes. For example, Wadud et al. (2016) argue that travel demand could go up substantially in an automated ownership future due to the reduction in generalized travel costs. Our results should not be substantially affected by this,[22] although these second-order effects can be a possible area for further research, e.g. to understand equity effects.

One area we have not investigated is the possibility where automation is available only as on-demand mobility options (OPAR and OEAR) due to higher costs of technology than used here (or regulations). This would mean that the time-use benefits may not be realized as privately owned vehicles are not fully automated anymore. On demand automated ride services will likely have a larger share in such a case, the upper end possibly limited by the higher costs.

More broadly, another area that would benefit from future research is a more in-depth assessment of the uncertainty (e.g. similar to Sobol's (1993) global sensitivity analysis) surrounding the estimates presented in this paper. While we have conducted a sensitivity assessment of the results with respect to some of the important input parameters, much less is known about the overall uncertainty of our results and similar types of estimates of adoption of automated vehicles or mobility services.

5. Factors affecting the least-cost option

Mileage, hours driven, and VTTS form an important part of the TCOU calculation, especially in the context of vehicle automation, and are therefore important factors in determining the relative cost-effectiveness of vehicle ownership as compared to on-demand mobility services (Wadud 2017, Davidson and Webber 2018). These variables in turn depend on other socio-economic factors. So far in this article, the analysis was conducted at a vehicle level, in order to understand whether vehicle ownership continues to be the least-cost option when FAVs and associated automated ride services become available. However, policymakers and researchers are often interested in understanding population's ownership and mobility choices, and the socio-economic characteristics associated with those. As such, the analysis is expanded to understand what socio-economic characteristics of the main driver of a vehicle are associated with a lower TCOU for ownership compared to automated on-demand ride services (or vice-versa), using the baseline findings detailed above. Table 4 presents

[22] In our approach, the positive utility derived from the same amount travel remains the same – so the least cost option gives the largest net utility, causing people to choose this option. Now, say, people start travelling more due to the lower relative cost of the chosen least-cost option, up to as much so that their total cost (time + money) is the same as before, then cost-wise there is no difference between the options. However, the utility of the new 'least-cost (but now equal cost + more travel)' option still is a higher utility option. So the choice does not change.

the cross-tabulation of the share of different alternatives with respect to some household and vehicle characteristics. However, given these group-wise characterizations often miss that there can be other underlying differences between the groups, we conduct a MNP (see section 3.5) regression analysis to model the probability of these alternatives being the least-cost alternative given the socio-economic and vehicle characteristics. Because of missing data for some of the predictors in the original dataset, the regressions are run on 7,167 observations (i.e. vehicles), instead of our original sample of 7,360.

Table 4. Share of different least-cost alternatives with respect to socio-economic characteristics

	Conventional fuel				Electric powered			
	PMDV	PAV	OEAR	OPAR	PMDV	PAV	OEAR	OPAR
Gender of main driver								
Male	20.1	46.7	16.6	16.6	9.8	46.0	23.8	20.4
Female	30.3	37.3	16.4	16.0	17.4	35.4	25.7	21.6
Presence of children								
No child	25.3	38.8	16.0	20.0	13.7	37.3	23.5	25.5
One/more children	23.8	50.6	17.8	7.9	12.4	49.9	27.4	10.3
Economic/job status								
Employed full time	15.2	57.9	13.0	13.9	7.6	54.8	19.5	18.1
Employed part time	35.1	35.9	16.4	12.6	20.7	35.7	26.1	17.5
Economically Inactive	37.4	16.5	23.2	22.9	20.1	18.1	33.7	28.2
Income groups								
0-4999	58.9	3.1	18.1	20.0	31.2	13.7	27.3	27.8
5000-9999	42.9	13.8	19.6	23.7	23.7	19.2	28.6	28.6
10000-14999	35.6	29.5	17.1	17.9	19.7	30.8	24.9	24.6
15000-19999	23.1	45.7	15.0	16.2	12.7	42.6	23.0	21.6
20000-24999	17.0	52.9	14.2	15.9	8.3	46.9	23.0	21.7
25000-29999	12.4	59.7	15.1	12.9	6.5	52.0	24.6	16.9
30000-39999	10.6	61.8	14.2	13.3	5.2	56.3	21.2	17.4
40000-49000	6.9	63.6	14.3	15.2	4.1	57.5	20.8	17.6
50000-59999	5.8	64.3	19.0	10.8	4.3	61.4	26.9	7.3
60000-74999	7.0	63.3	19.1	10.6	0.8	63.3	25.5	10.4
75000-99999	4.2	64.2	25.1	6.5	1.1	62.0	30.2	6.7
100000-124999	2.1	70.7	13.6	13.5	2.1	63.0	21.4	13.6
125000+	0.6	69.0	22.7	7.8	0.0	58.9	32.9	8.2
Location of HH*								
Inner London	21.6	30.3	27.6	20.5	8.6	31.9	35.1	24.3
Outer London built-up	24.9	35.1	20.5	19.4	9.7	34.4	30.0	25.9
West Midlands built-up	20.0	40.0	21.7	18.3	15.4	36.3	28.3	20.0
Greater Manchester built-up	19.3	43.4	17.4	19.9	10.6	38.3	26.7	24.4
West Yorkshire built-up	23.8	46.2	14.0	16.1	14.0	38.5	28.0	19.6
Liverpool built-up	27.3	30.9	20.0	21.8	14.5	29.1	29.1	27.3
Tyneside built-up	22.0	40.4	17.4	20.2	11.0	37.6	29.4	22.0
South Yorkshire built-up	18.6	52.9	20.0	8.6	14.3	48.6	25.7	11.4
Other urban – over 250k population	24.0	41.7	18.7	15.6	11.7	41.8	26.6	19.9

Other urban – 100 k to 250k population	28.2	39.9	15.5	16.4	18.0	36.9	24.0	21.0
Other urban – 50k to 100k population	28.6	36.6	18.1	16.7	15.1	38.0	26.5	20.4
Other urban – 25k to 50k population	24.8	43.3	15.2	16.7	13.6	40.2	23.4	22.8
Other urban – 10k to 25k population	25.7	41.8	17.0	15.6	15.7	41.2	23.9	19.2
Other urban - 3k to 10k population	24.6	46.0	13.5	15.9	15.0	44.6	21.1	19.3
Rural	26.9	44.2	14.6	14.2	13.1	45.6	22.2	19.0

* the sample size in some of these areas could be too small to be representative

We combine the two on-demand ride service options to create a non-ownership alternative, resulting in three alternatives for the least-cost TCO: private manually-driven vehicles (PMDV), privately-owned automated vehicles (PAV) and automated on-demand ride services.[23] Table 5 presents the results of the MNP regression to explain the probability that one of these three options is the least-cost one – for the conventionally-fuelled and electric options separately.[24] A comparison of the log-likelihoods for the chosen models and corresponding constant-only models shows significantly better fits for the chosen models using the likelihood ratio test (Table 5).

The base option is when owning the manually-driven vehicles (PMDV) is the least-cost option. As can be expected, the income of the main driver is a key explanatory factor: firstly, car ownership and car travel demand (and as such vehicle mileage and time spent travelling) generally increases with income (Goodwin et al. 2004, Becker et al. 2017) and, possibly more importantly, income substantially affects VTTS and savings through useful use of time. Therefore greater income is associated with higher likelihood that FAV ownership (i.e. PAV) will be cheaper, and as such potentially more attractive, option. This pattern is clear in both the bivariate tabulation (Table 4) and MNP regression analysis (Table 5). Greater income also increases the likelihood for on-demand automated mobility services to be more attractive compared to manually-driven vehicle ownership. This shows that even modest savings through higher usefulness of travel time can be large enough to make automated mobility services competitive with privately-owned manually-driven vehicles.

[23] A four-alternative version was estimated, but is not reported, as the three-alternative version fits the data significantly better. Two-alternative versions with no manually driven vehicles were also estimated as a potential future scenario. Results are available from the authors on request.
[24] Although MNL or MNP regression is often used in choice modelling context, they are a statistical tool to understand discrete possible outcome, see e.g. Bwamballe et al. (2019) for an application outside of choice modelling.

Table 5. Parameter estimates for MNP model for FAV ownership (PAV) and automated on-demand ride services (OEAR and OPAR) to be the least cost option compared to PMDV

	Conventional fuel AV		Electrically powered AV	
Explanatory factors	coefficient	t-stat	coefficient	t-stat
Ownership (PAV)				
Female main driver [base: male]	-0.126	-2.12	-0.326	-5.22
Multiple adult in HH [base: 1 adult]				
Children in HH [base: no children]	0.154	2.63	0.131	2.43
Multiple vehicle in HH [base: 1 vehicle]	0.210	3.18	0.461	5.38
Second car [base: first car]	-0.427	-5.90	-0.611	-7.04
Ln(Income of main driver)	1.096	28.09	0.614	19.86
Ln(Age of vehicle)	-0.132	-3.75		
Ln(Age of main driver)	-7.908	-4.67	-0.701	-7.03
Ln(Age of main driver) squared	0.957	4.18		
Working status [base: not working]				
Main driver working full time	0.519	6.44	0.483	7.77
Main driver working part time	0.211	2.27		
Location of HH [base: other urban]				
HH in rural area	0.156	2.34	0.247	3.50
HH in Inner London	-0.483	-2.58		
HH in Outer London	-0.230	-2.49		
Ln(Vehicle CO2)			0.825	9.78
Vehicle used for business [base: not used]	1.662	15.82	1.264	19.00
Main driver blue badge holder [base: not]				
Constant	5.628	1.85	-6.901	-10.98
Mobility services (OEAR and OPAR)				
Female main driver [base: male]	-0.203	-3.55	-0.211	-3.46
Multiple adult in HH [base: 1 adult]	-0.670	-10.12	-0.583	-8.72
Children in HH [base: no children]				
Multiple vehicle in HH [base: 1 vehicle]			0.193	2.18
Second car [base: first car]	0.679	11.43	0.459	5.29
Ln(Income of main driver)	0.328	13.36	0.259	10.48
Ln(Age of vehicle)	-0.809	-22.84	-0.590	-21.43
Ln(Age of main driver)	-8.225	-6.03	-6.507	-5.48
Ln(Age of main driver) squared	1.116	6.15	0.875	5.53
Working status [base: not working]				
Main driver working full time				
Main driver working part time	-0.246	-3.40	-0.262	-4.09
Location of HH [base: other urban]				
HH in rural area	-0.237	-3.62	-0.173	-2.50
HH in Inner London	0.736	4.38	0.915	6.59
HH in Outer London	0.235	2.76	0.434	6.17
Ln(Vehicle CO2)	1.647	19.12	1.729	18.10
Vehicle used for business [base: not used]	0.360	3.22		
Main driver blue badge holder [base: not]	0.309	2.87	0.284	2.56
Constant	5.635	2.26	3.172	1.44
Log likelihood – model	-5774.46		-5701.96	
Log likelihood – constant only	-7738.45		-7131.38	
AIC	11608.9		11455.9	
N	7167		7167	

Having the main driver live in London reduces the likelihood that ownership of automated vehicles, i.e. PAV, will be the lowest cost option for conventionally fuelled vehicles, compared to other urban areas in the UK.[25] This can be interpreted as follows: London has an excellent public transport network; as such vehicles there are not used as much as those in other UK urban areas (Chatterton et al., 2015), and ownership of PAVs is less likely to be the cheapest option. Inner London has the most extensive public transport services, meaning the owned vehicles are used substantially less compared to outer London (and areas outside of London). As such the vehicles in inner London are more expensive on a per mile basis, and PAVs are even less likely to be the most attractive option than in outer London. On the other hand, in rural areas, where vehicles are generally driven for longer distances given the absence of transport alternatives, a PAV is more likely to be more cost-effective than a PMDV. For the same reason, the findings for the automated mobility services is just the opposite: they are the least likely to be the cheapest option in rural areas, and are the most attractive for Inner London.

If the vehicle is primarily driven by a female, then both PAVs and automated on-demand mobility services are less likely to be cheaper than PMDVs – possibly reflecting a general pattern of lower car travel by female 'main drivers'. Larger household size reduces the likelihood that automated on-demand services will be the cheapest option. This is possibly because total travel in multi-adult households is likely to be larger, making ride services less attractive. The presence of children in the household also increases the likelihood of owning an automated vehicle compared to owning a manually-driven one.

Presence of multiple vehicles in the household increases the likelihood of automated vehicle ownership. More importantly, if a vehicle is not the main household car, then it is less likely for PAVs to be the cheapest option for that car, and more likely that automated on-demand services will be the least expensive choice. This can be explained by the lower mileage of 'secondary cars', and generally lower income of the main driver of the secondary car in the household.

Full-time and part-time workers both have a greater probability of finding ownership of an automated vehicle (PAV) to be less expensive compared to a PMDV, with full-time workers even more likely than part-time ones. Part time workers are less likely to find automated on-demand services cheaper than PMDVs. As can be expected, if a vehicle is used for business trips, then it is cheaper to own automated vehicles (PAV) than PMDVs. Clearly, business VTTS is substantially higher than VTTS for commuting and other uses, and therefore the travel time use-related benefits of FAVs

[25] In the model specification phase, we had included other area type classifications among the predictors, including population density of the residential area. The model presented here is retained as the best fit to the data.

increase if a vehicle is used for business travel. Although less attractive than PAVs, business use still increases the attractiveness of on-demand mobility services over PMDVs, for its ability to provide some time use-related benefits.

The higher carbon emissions of currently owned vehicle mean higher fuel consumption and running costs. Therefore, owners of such inefficient vehicles find automated mobility services cheaper than both PMDVs and PAVs. On the other hand, current ownership of older vehicles results in lower depreciation costs, making PAVs less attractive than PMDVs, cost-wise. It is important to note that this is an artefact of how we have modelled the TCOUs, as we have added constant costs of 'automation' to present day TCOUs of owned vehicles.

After controlling for income, household size, and gender, the likelihood to own or use automated vehicles decreases with increasing age of the main driver. While blue-badge holding of the main driver for disabilities does not have any statistically significant effect for automated vehicle ownership (removed from specification), it increases the likelihood that automated mobility services would be less expensive than PMDVs. However, blue-badge holders will possibly have other non-economic incentives to own automated vehicles (Wadud et al. 2016, Harper et al. 2016).

For the regression involving electric automated options (ownership or mobility services), model fit is poorer than for the regression using conventionally-fuelled vehicles. Although the parameter estimates for the electric options somewhat differ from those for the conventionally fuelled options numerically, qualitatively there is no substantial divergence. The parameter estimates have similar signs as conventionally fuelled vehicles for all significant variables for both electric options – ownership and mobility services. However, business-use of the vehicles was not an important predictor for automated electric mobility services. Age of the vehicle and part-time working status of the main driver were not significant predictors for automated electric vehicle ownership. While electric PAVs are still more likely to be least-cost in rural areas compared to conventionally fuelled PMDVs, they are no less likely in London (relative to PMDVs).

6. Conclusions

In this paper, we have estimated and compared the costs of ownership and use of privately-owned human-driven and automated vehicles with automated on-demand mobility services using UK's NTS data. As such, our results reveal what share of the current vehicle fleet could be replaced by automated vehicles (whether owned or provided by mobility services) from a user cost perspective. We add to previous research by taking into account the heterogeneity in the individual vehicles' mileage, age and cost profile as well as users' values of travel time. While our analysis is limited to existing vehicles and their travel characteristics, the approach can be extended further to include other transport modes, if the costs and usage of those modes is included to understand potential uptake of FAVs in general.

Our results show that, although automated on-demand mobility services will become more cost-efficient compared to owned automated vehicles in some cases, ownership will remain the least-cost option in as many, if not more, cases. Even in our most pro-mobility services sensitivity analysis, with high utilization of on-demand vehicles and electric propulsion, nearly one-third still would find ownership (of PAVs and PMDVs) to be the least cost option. In *all* the other sensitivity tests, ownership (both PAVs and PMDVs) continues to be more attractive for at least half (and in some cases up to two-thirds) of the current fleet. These shares are based purely on out-of-pocket and time costs, and do not consider trust in technology and other psycho-social factors. Inclusion of these additional factors would likely increase the attractiveness of ownership, especially of manually driven vehicles (PMDVs), even further. Thus, if anything, our study is likely to provide rather conservative estimates of the prevalence of FAV private ownership. Indeed, in the only scenario where we took into account the possibility of a uniformly perceived convenience of owning a private vehicle – whether automated or manually driven – the ownership share reaches four-fifths of the vehicle fleet. Other factors not taken into account here, such as the reluctance to share the vehicle space with strangers in the wake of the Coronavirus (COVID-19) pandemic (Bhaduri et al. 2020), may reduce the appeal of shared or pooled automated ride services even further.

Overall, our results suggest that, left to its own devices, consumer demand for AVs may still follow a traditional private ownership model, and a near total transition to automated ride services is *not* a foregone conclusion. At the same time, our analysis suggests that automated ride services would likely be the cheaper option for a non-negligible share (one-thirds to three-fifths) of the vehicle fleet in all scenarios considered, which can still have large implications for the transport and vehicle manufacturing industry.

The second part of our analysis reveals that higher income and business use of vehicles lead to a higher likelihood of owning automated vehicles or using automated on-demand mobility services, compared to manually-driven vehicle ownership. Our results also reveal the economic appeal of replacing the second or third vehicle in the household with automated mobility services. Ownership of automated vehicles is more likely in rural areas, whereas in large urban centres like London on-demand mobility services will be least-cost. This highlights the heterogeneity with respect to socio-economic, demographic and locational factors in the potential adoption and use of automated vehicles or automated mobility services. Such heterogeneity in adoption pattern raises important questions about the equity implications of vehicle automation and related policy decisions, e.g. if infrastructure is developed for exclusive or priority use of automated vehicles. Equity related impacts require further investigation, as others have suggested too (Cohn et al., 2019; Milakis & van Wee, 2020).

Importantly, among automated on-demand ride services, exclusive use services (OEAR) are cost-effective for more cases than pooled ride services (OPAR) in all our sensitivity tests, primarily due to the possibility of better use of time in OEARs. Given the potential for a reduction in vehicle miles through sharing in OPAR vehicles but an increase in vehicle miles through empty running of OEAR vehicles, a larger OEAR share may have adverse energy, carbon and traffic impacts. Combined with recent suggestions that vehicle automation may increase demand (Arbib and Seba 2017), and evidence of modal switch from public transport and active modes to existing on-demand ridehailing or ridesharing services (Clewlow and Mishra 2017), this raises the possibility that the net environmental and traffic consequences of automated mobility services could indeed be undesirable. Travel demand from owned automated vehicles will also likely increase in response to larger comfort and useful use of time (Wadud et al. 2016). This possibly suggests the need for a more interventionist governance approach in order to align the diffusion of FAVs with broader social and environmental policy goals (Docherty et al., 2018). The design of measures in this vein could benefit from the analysis presented in this paper, as it identifies points of intervention for making pooled automated ride services more attractive from a TCOU perspective.

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