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Why would people want to travel more with automated cars?

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ABSTRACT

The use of automated vehicles (AVs) may enable drivers to focus on non-driving related activities while travelling and reduce the unwanted efforts of the driving task. This is expected to make using a car more attractive, or at least less unpleasant compared to manually driven vehicles. Consequently, the number and length of car trips may increase. The aim of this study was to identify the main contributors to travelling more by AV.

We analysed the L3Pilot project's pilot site questionnaire data from 359 respondents who had ridden in a conditionally automated car (SAE level 3) either as a driver or as a passenger. The questionnaire queried the respondents' user experience with the automated driving function, current barriers of travelling by car, previous experience with advanced driving assistance systems, and general priorities in travelling. The answers to these questions were used to predict willingness to travel more or longer trips by AV, and to use AVs on currently undertaken trips. The most predictive subset of variables was identified using Bayesian cumulative ordinal regression with a shrinkage prior (regularised horseshoe).

The current study found that conditionally automated cars have a substantial potential to increase travelling by car once they become available. Willingness to perform leisure activities during automated driving, experienced usefulness of the system, and unmet travel needs, which AVs could address by making travelling easier, were the main contributors to expecting to travel more by AV. For using AVs on current trips, leisure activities, trust in AVs, satisfaction with the system, and traffic jams as barriers to current car use were important contributors. In other words, perceived usefulness motivated travelling more by AV and using AVs on current trips, but also other factors were important for using them on current trips. This suggests that one way to limit the growth of traffic with private AVs could be to address currently unmet travel needs with alternative, more sustainable travel modes.

1. Introduction

Automated Vehicles (AVs) will free drivers from the driving task (SAE levels 3–5) (SAE International, 2018), enabling them to focus on non-driving related activities while travelling. Thanks to digitalisation, many work or personal tasks could thus be dealt with while travelling (Wardman et al., 2020). Travellers could also spend the time in a more relaxed manner, such as "talking with fellow passengers" and "observing the landscape" (Nordhoff et al. 2020). Automation could thus increase the productive use of travel time and

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enhance the intrinsic value of travel, such as having 'time out' or enjoying the trip (Singleton, 2019). For an individual traveller, this could make it more attractive or less unpleasant to spend time travelling by car.

Automated driving (AD) will also reduce the *unwanted efforts* of driving, meaning cognitive or physical efforts needed by the manual driving task that the driver would prefer not to exert (Cornet et al., 2021). Unwanted efforts may act as a barrier to travelling by car. For example, some drivers avoid congested traffic or parking in confined spaces (Beirão & Sarsfield Cabral, 2007; Higgins et al., 2018). By removing (fully automated, SAE level 5) or reducing (conditional to high automation, SAE levels 3 and 4) these unwanted efforts, AVs could make it easier to address travel needs.

Due to improved travel experience with AD, travellers may be willing to replace existing non-car trips with car trips, accept longer travel times by car, or even perform new trips by car (Lehtonen, Malin, et al., 2021; Lehtonen, Wörle, et al., 2021; Moore et al., 2020; Nielsen & Haustein, 2018; Soteropoulos et al., 2019). No direct data are yet available on the realised impact of AVs on travel behaviour, but the mechanism causing the impact is well justified. For example, in the context of rail traffic, Wardman et al. (2020) demonstrated that possibilities for digital multitasking increased travel demand. Hardman (2021) interviewed current users of SAE level 2 driving systems (i.e., combining lateral and longitudinal driving assistance systems) who stated that the system helped them make longer trips by car and replace air trips with car trips. Based on stated preferences given after experiencing simulated AD (SAE level 3 or 4), Lehtonen et al. (2020) found that self-rated travel experience with AVs was positively associated with willingness to make more or longer trips by AV.

More formally, the impact of AVs on travel demand could be modelled through the value of travel time savings. AVs could yield savings by increasing the utility of travel time by enabling better engagement in non-driving related activities (Childress et al., 2015; Kröger et al., 2019; Wardman et al., 2020). Some authors, however, prefer to use the term worthwhileness of travel time to emphasise the non-monetary aspects of utility, such as enjoyment, relaxation, or fitness gained through travelling (Cornet et al., 2021).

Because AVs can increase travelling by car only if they are used in the first hand, factors affecting the willingness to use AVs in general are also potential contributors to increased travel. Technology acceptance models recognize *perceived usefulness* and *perceived ease of use* as important determinants of actual and intended use of technology in general and AVs in particular (Davis et al., 1989; Nordhoff et al., 2020; Venkatesh et al., 2003; Xu et al., 2018; Zhang et al., 2019).

In addition, trust in automation, perceived safety, and previous experience with advanced driving assistance systems (ADAS) have been linked to a higher willingness to use AVs (Louw et al., 2021; Nielsen & Haustein, 2018; Nordhoff et al., 2020; Xu et al., 2018; Zhang et al., 2019). Many, but not all, studies have also associated younger age with a higher willingness to use AVs (Haboucha et al., 2017; Liljamo et al., 2018; Nordhoff et al., 2020). Being male is often found to predict a higher willingness to use AVs, but also the opposite has been observed (Anania et al., 2018; Liljamo et al., 2018; Nordhoff et al., 2020). Living in an urban environment has been linked to a higher willingness to use AVs (Liljamo et al., 2018), possibly because urban drivers need to cope with congested traffic and limited parking more often than rural drivers.

A particular challenge to understanding the effects of AVs is that very few people have yet had any direct experience with higher levels of AD. Most studies have only provided participants with descriptions of AVs and relied more or less on the respondents' imagined AV experience (e.g., Nordhoff et al., 2020). To address this, some studies have used simulators to provide a more realistic AV experience (e.g., Lehtonen, Wörle, et al., 2021), or the participants have ridden in an AV on a test track (e.g., Xu et al., 2018). Some studies have also used fully automated cars or shuttle buses in real world conditions (e.g., Molina et al., 2021; Nordhoff et al., 2019). The current study was part of the EU-funded project L3Pilot, which was novel in that the participants experienced conditionally automated passenger cars driving in real traffic.

Many existing studies have focused on willingness to use AVs. However, they seldom distinguish between using AVs on currently undertaken trips and making new kinds of trips. From a transport system perspective, increased car travel could pose sustainability challenges, because it may offset the potential traffic efficiency and energy savings of AD (Bjorvatn et al., 2021; Sonnleitner et al., 2021; Soteropoulos et al., 2019; Wadud et al., 2016). To design effective policy measures to maximise the positive and minimise the negative effects, it is of utmost importance to identify the most important contributors to increasing car travel once AVs become available. To address this shortcoming, the current study queried the willingness to travel more or longer trips by AV, in addition to using the AV on currently undertaken trips.

1.1. Aims of the study

Identifying the contributors to travelling more by AV is important for understanding their potential impact on mobility and the transport system. The current study investigates the willingness to travel more or longer trips by AV and, for comparison, investigates the willingness to use AVs on currently undertaken trips. This was investigated based on the questionnaire data collected among participants who had experienced a conditionally automated (SAE level 3) car in a motorway or urban context.

The main contributors to the aforementioned potential mobility impacts were identified by modelling the relationships between the impacts and a set of potential predictor variables in the questionnaire. The potential predictor variables covered the self-rated travel experience with the AV, current travel behaviour, experience with ADAS, and sociodemographic indicators (gender and age). Factors such as whether the test was performed on a motorway or in urban settings, or whether the participant was a professional safety driver or an ordinary (non-professional) car driver, were also considered.

The main contributors to travelling more by AV and using AVs on current trips were identified with a data-driven approach. A Bayesian cumulative ordinal regression models were fitted to the data with a regularised horseshoe prior (Piironen & Vehtari, 2017). The regularised horseshoe prior shrinks the less important model terms towards zero, effectively creating a sparse model with the most important predictors left. Such *penalised* models are less affected by the noise in the data and provide a better prediction accuracy than unpenalised models.

2. Methods

2.1. Participants and procedure

A total of 479 persons participated in the pilots and experienced a conditionally automated car as part of the L3Pilot project (Weber et al., 2021). The participants were either employees of the companies testing the systems or recruited via their local contacts. They were either professional safety drivers who were very familiar with the vehicle they tested, or ordinary (non-professional) car drivers. For safety reasons, in urban settings all participants except professional safety drivers sat in the passenger seat, as the professional drivers were needed to handle takeovers. All participants had a valid driver's licence. All participants gave informed consent to participate in the data collection. All the pilots were conducted according to local regulations, and ethical approval was sought when needed.

The tested systems were either Motorway or Urban Automated Driving Functions (ADFs). When active, the motorway and urban ADFs took care of longitudinal and lateral control of the vehicle, allowing the driver to engage in other activities. When the ADF reached the limits of its Operational Design Domain (ODD), a takeover request was issued, and the driver had to take over control of the car. The Motorway ADF could operate up to 130 km/h in an automated mode within the ODD of the system. The participants tested the Motorway ADF both in free-flowing and congested traffic. The Urban ADFs were tested on an urban road network with a speed limit of up to 50 km/h. The ODD of the Urban ADFs also included intersections, with a few exceptions defined in the testing permissions.

Most of the pilots were conducted during a 1 to 1.5-hour drive over distances ranging from 60 to 133 km. However, some drives were as short as 30 min and others as long as 6 h. In some of the pilots, the participants could take their eyes, hands, and mind off the driving task while the ADF was activated and engage in other tasks. In other pilots this was not allowed. During the pilots, this consisted mostly of smartphone use and looking at scenery. Before and after experiencing the ADF the participants answered questions in the L3Pilot pilot site questionnaire, described in detail in the next section (2.2).

The data from 479 participants were filtered for missing or out-of-range values. Participants aged under 18 or above 100 years (n = 2) were excluded, as they would not represent typical car drivers. A response was categorised as missing if the scale contained a response option such as "I don't know" or if the value had not been provided: Either the pilot site had not included the question in their local version of the questionnaire, or the data were not available for some other reason. After filtering, data from 359 respondents (75%) were available for analysis (Table 1).

2.2. Pilot site questionnaire

The first part of the questionnaire, administered before experiencing AD, started with sociodemographic questions and continued with questions on the current travel behaviour and prior experience with ADAS. The respondents also provided information on their year of birth, gender (male, female, other), and whether they had attended an urban or a motorway ADF pilot site. The questions investigated in the current study are described below.

The participants answered how often they used a car on a four-step scale, where 1 = "(Nearly) Every day", 2= "3–5 days/week", 3 ="1–2 days/week", and 4 = "Less often or never". Unmet travel needs, which conditionally automated cars could potentially address, were queried with eight questions (Table 2). The reasoning behind the questions was that if a question regarding unmet travel needs predicted willingness to travel more or longer trips, then the ADF could be interpreted to help meet the unmet travel need. The first question asked whether respondents would travel more in their daily life if travelling were easier. If the question predicted travelling more, the respondents would probably consider that ADF makes travelling easier. Experienced lack of time for travelling could be addressed by an ADF if the ADF could let the driver engage in travel-based activities. Other questions related to unmet travel needs were focused on barriers to current car use, which ADFs could potentially address. The two traffic jam questions were averaged to form a scale, as the answers regarding traffic jams affecting route choice and timing were strongly correlated (rho = 0.58), and route and timing can be seen to be intrinsically related. There were also three questions on adverse conditions affecting current car use.

The participants also answered three questions describing their priorities (i.e., cost, efficiency, comfort) when travelling in general (Table 3). Respondents were further asked how often they drive a car on a scale where 4 ="(Nearly) Every day", 3 = "3–5 days/week", 2 = "1–2 days/week", and 1 = "Less often or never".

Table 1
Number of participants per ADF, test type, and driver type. Percentage of males and females, and average age (standard deviation in parentheses) given per group.

ADF	Test type	Driver type	N	Males / Females (%)	Age in years (M and SD)
Motorway	On road	Ordinary driver	150	81 / 19	40 (11)
		Professional safety driver	40	83 / 18	44 (10)
	Wizard-of-Oz[1]	Ordinary driver	32	72 / 28	40 (11)
Urban	On road	Ordinary driver (in passenger seat)	134	63 / 37	40 (12)
		Professional safety driver	3	67 / 33	29 (1)

[1]The vehicle is controlled by an experimenter using hidden controls without informing the participant, giving the impression of automated driving.

Table 2
Questions and scales related to unmet travel needs.

Variable/scale	Question(s)	Response scale
Travel more if easier	I would travel more in my daily life if travelling were easier.	
Lack of time	Lack of time greatly affects my daily travel choices.	1 = Strongly disagree
Traffic jams (mode)	Traffic jams affect my choice of mode.	
		2 = Disagree
Traffic jams (route and timing)	Traffic jams affect my choice of route in the car.	3 = Neutral
(Cronbach alpha = 0.73)		4 = Agree
	Traffic jams affect the time at which I choose to make my trips.	5 = Strongly agree
Adverse conditions: Weather	Weather conditions affect my decision to drive.	6 = Don't know (coded as missing)
Adverse conditions: Darkness	Darkness affects my decision to drive.	
Adverse conditions: Fatigue	Fatigue affects my decision to drive.	

Table 3
Questions related to priorities in travelling.

Variable	Question	Response scale
Low price	I tend to select the cheapest mode of transport, even if it would take more time.	1 = Strongly disagree
Short time	I tend to select the quickest mode of transport, even if it would cost me more.	
Comfort	I tend to select the most comfortable mode of transport.	2 = Disagree
		3 = Neutral
		4 = Agree
		5 = Strongly agree
		6 = Don't know (coded as missing)

The respondents were asked to describe their experience with existing ADAS. A list of eight ADAS was given: Parking assist, Self-parking, Cruise Control (CC) or Adaptive Cruise Control (ACC), Blind Spot Monitoring (BSM), Lane Departure Warning (LDW), Lane Keeping Assistance (LKA), and Forward Collision Warning (FCW). Those who indicated that they had the system in their current vehicle and were using it were coded as one, otherwise as zero.

The second part of the questionnaire, filled in after experiencing AD, focused on the mobility impacts and experience with ADF. The participants rated their willingness to travel more or longer trips if they had the respective ADF in their car. Similarly, they were asked to rate the willingness to use the ADF as part of their current trips (Table 4). These three questions were used as mobility impact variables.

Participants' experience with the ADF was queried in a multiple-choice format, from which seven scales were constructed (Table 5). Participants' willingness to engage in non-driving related activities was measured by asking them to rate how often they would like to perform different activities during AD. Of 15 activities rated, the analysis focused on 10 which conditionally automated cars would make considerably easier by allowing the driver to take their eyes off the road and hands off the wheel (Table 5). The *Leisure activities* score was calculated as an average of the following: Texting, Interacting with a passenger, Eating or drinking, Calling, Personal hygiene/Cosmetics, Smartphone apps, Social media, Browsing the Internet, and Watching movies. Office/work tasks was used as the *Work activities* score. A higher score indicated a higher willingness to engage in activities during AD.

Participants also evaluated the ADF using van der Laan's (1997) *Usefulness* and *Satisfaction* scales (Table 4). Usefulness and satisfaction scores were calculated as averages after converting the responses so that higher values always represented a positive evaluation. In addition, three factors were formed from other questions to measure *Trust in ADF* and *Workload with ADF* and *Predictability of ADFs*. The factors were formed by grouping thematically similar questions together (Table 5).

The participants were also asked about their experience of motion sickness. Of 359 participants, 10 stated that when the ADF was activated they felt "slightly nauseated" and none "severely nauseated". The rest reported no signs of motion sickness. Despite its low prevalence among the participants, motion sickness was included as one of the predictors.

2.3. Analysis

The aim of the analysis was to identify the most important predictors for the mobility impacts and assess their relative strengths. Arguably, a standard way to identify the most important variables would be to run a regression model with all the predictors and then look for significant coefficients. A cumulative regression ordinal regression model is suitable for the current outcome variables, although linear regression models also often satisfactorily identify the strength of associations between predictors and outcomes. However, the current data were pooled from multiple experiments performed at different sites with similar, but not equivalent, vehicles and test environments. The source of the individual data points was not available to prevent benchmarking individual systems. Under these circumstances, the data show a lot of test site dependent variation, should be considered as noise in the statistical model. The noise in the data is a problem for obtaining a generalisable model, because standard regression models are prone to overfit to their training data, meaning that the coefficients are influenced by the noise in the data (McNeish, 2015).

Overfitting can be addressed by using a penalised regression, such as lasso regression, where the coefficients are shrunk toward and

Table 4
Mobility impact questions.

Impact variable	Question	Response scale
More trips	I would make MORE trips if I had the function in my car.	1 = Strongly disagree
Longer trips	I would select destinations further away if I had the function in my car.	2 = Disagree
		3 = Neutral
Current trips	I would use the system during my everyday trips.	4 = Agree
		5 = Strongly agree
		6 = Don't know (coded as missing)

Table 5
Questions and scales related to travel experience.

Scale	Questions	Response scale
Leisure activities	How often would you engage in the following activities while the system is active:	6 = Very frequently
	Texting	5 = Frequently
	Interacting with a passenger	4 = Every now and then
	Eating or drinking	3 = Infrequently
	Calling	2 = Very infrequently
	Personal hygiene/Cosmetics	1 = Never
	Smartphone apps	
	Social media	
	Browsing the Internet	
	Watching movies	
Work activities	How often would you engage in the following activities while the system is active:	
	Office/work tasks	
Usefulness	I think that the tested system was …	Five-step scale from 1 to 5
(Cronbach's alpha = 0.71)	Useful – Useless (reversed)	
	Bad – Good	
	Effective – Superfluous (reversed)	
	Assisting – Worthless (reversed)	
	Raising alertness – Sleep-inducing	
Satisfaction	I think that the tested system was …	
(Cronbach's alpha = 0.86)	Pleasant – Unpleasant (reversed)	
	Nice – Annoying (reversed)	
	Irritating – Likeable	
	Undesirable – Desirable	
Trust in ADF	I felt safe when driving with the system active	1 = Strongly disagree
(Cronbach's alpha = 0.85)		
	Driving with the system active was comfortable	2 = Disagree
		3 = Neutral
	I trust the system to drive	4 = Agree
Low workload of ADF	Driving with this system was difficult (reversed)	5 = Strongly agree
(Cronbach's alpha = 0.84)		6 = Don't know (coded as missing)
	Driving with this system was demanding (reversed)	
	Driving with this system was stressful (reversed)	
Predictability of ADF	Sometimes the system behaved unexpectedly (reversed)	
(Cronbach's alpha = 0.85)		
	The system worked as it should	
	The system acted appropriately in all situations	
Motion sickness	Did you experience motion sickness during your test drive with the function active?	0 = No signs of motion sickness
		1 = Slightly nauseated

to zero (Tibshirani, 1996). This reduces overfitting and also identifies the most important predictors. A drawback of lasso regression is that obtaining correct standard error estimates for the lasso regression coefficients is not straightforward (Tibshirani, 1996).

Penalisation can be naturally performed in a Bayesian linear model using shrinkage priors (van Erp et al., 2019). The coefficients in Bayesian regression are represented as probability distributions. A shrinkage prior forces the coefficients of less important predictors toward zero probability, but as the probability distribution of a coefficient can never be exactly zero, it is always possible to assess the uncertainty of the estimate using the posterior distribution and credibility intervals describing it.

When the coefficients of less important predictors are shrunk, also a sparse model (i.e., a model with fewer predictors than originally) is identified. However, as the probability will never be exactly zero, an additional step is needed for selecting a discrete set of variables (van Erp et al., 2019). One possibility would be to include predictors with a credibility interval that does not contain zero—how large it should be is another question. It could be argued that a 50% credibility interval would suffice, as it would mean that the probability of having either only positive or negative coefficients is more than 50% (Narisetty & He, 2014). However, the best credibility interval size for predictive accuracy depends on the prior and model (van Erp et al., 2019)[1].

For the current analysis, a 60% credibility interval was used instead of 50%, because then the models were easier to interpret, as some of the weaker coefficients were not selected. After selecting the predictors, also *relaxed models* were fitted: Using only the selected variables identified with the help of the shrinkage priors, the models were fitted with the same non-shrinkage priors as the unpenalised models.

To confirm that the penalised regression was able to identify the most predictive subset of predictors, the unpenalised, penalised, and relaxed models were compared for their prediction accuracy using leave-one-out (LOO) cross-validation (Vehtari et al., 2017). Expected log pointwise predictive density (ELPD) was used as a measure for prediction accuracy.

The predictor values were standardised before modelling. Means, standard deviations, minimums and maximums of the unstandardised outcome and predictor variables are reported in Supplementary Table 1. All analyses were performed in R (v. 4.0.4). Bayesian modelling was performed using the package *brms* (v. 2.15.0). Cumulative ordinal regression models with logit link function were used. For unpenalised and relaxed models, an uninformative normal priors with $M = 0$ and $SD = 10$ were used for the predictors. For the penalised models, a regularised horseshoe prior was used. All models had four chains with 2000 iterations of which 1000 were used as warmup. All models converged ($\hat{R} = 1.00$) and there were no divergences after the warmup.

3. Results

3.1. Mobility impacts

The responses to the outcome variables are shown in Fig. 1. For making more trips, the share of those who responded “strongly agree” or “agree” (25%) was about half of those who responded “strongly disagree” or “disagree” (51%). For making longer trips, the share of respondents strongly agreeing or agreeing (39%) and strongly disagreeing or disagreeing (42%) was similar. Eighty-one percent of the participants agreed or strongly agreed with using the ADF on trips they currently make, and only 9% strongly disagreed or disagreed. Only a minority of participants agreed or strongly agreed on making more trips (10%) or longer trips (14%) but did not agree or strongly agree on using ADF on current trips.Fig. 2.

3.2. Predictors of mobility impacts

The penalised model had a better predictive accuracy than the unpenalised model (Table 6), showing that the penalisation was able to achieve a model which generalises better. The most important predictors were selected (the 60% rule) and a relaxed model was fitted (unpenalised model with only the selected predictors). The relaxed model had the best predictive accuracy (Table 6) confirming that the selected variables could be used to predict mobility outcomes. The full summaries of the models are given in the Supplementary Material.

Willingness to travel more or longer trips by AV were positively associated with many of the same predictors. Willingness to engage in *Leisure activities* during AD and experienced *Usefulness* were among the strongest predictors. More and longer trips were also predicted by *Travel more if easier*, *Darkness,* and *Fatigue,* indicating that respondents experienced that they had some currently unmet travel needs.

Experience with CC/ACC was negatively associated with willingness to make more or longer trips. Participants from the *Urban pilot* were more willing to travel longer trips than others.

Willingness to use AVs on current trips had somewhat different predictors. Willingness to use on the current trip was positively associated with many of the travel experience related predictors: *Usefulness, Trust in ADF, Leisure activities,*and*Satisfaction* in order of magnitude.

Experiencing *Traffic jams affecting route and timing* increased the willingness to use ADF on current trips, as well as being an experienced user of the *Parking assist* system. Being female, an urban pilot participant, a professional driver, or a frequent driver were all negatively associated with willingness to use AVs on current trips.

Of the travel priorities, only making more trips was positively associated with prioritising *Low price* in travel mode choices.

The relationship of the mobility outcomes variables and selected predictor variables are shown in Fig. 3 using the original scales.

4. Discussion

The current study investigated the potential mobility impacts of conditionally automated cars. We identified contributors to undertaking more or longer trips by AV and using AVs on current trips. One-fourth (25%) of respondents were willing to make more trips with AVs, while four out of ten (39%) were willing to make longer trips. A large majority (81%) were willing to use AVs on current trips.

The results indicate that conditionally automated cars have a substantial potential to increase travelling by car, even though a

[1] Alternatively, a projective prediction method could be used (Piironen et al. 2020), but at the moment this is not available for cumulative logit models.

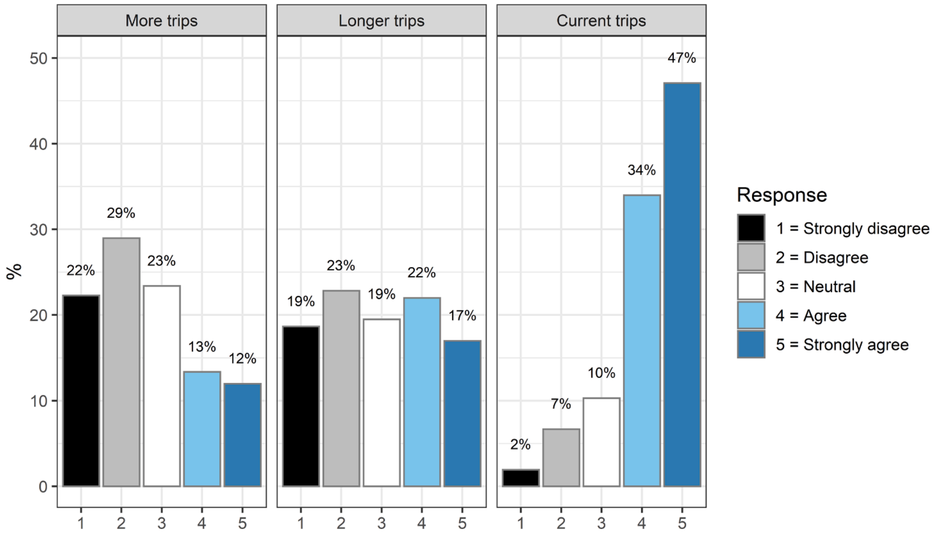

Fig. 1. Responses to questions on making more trips or longer trips by AV, and on using AVs on current trips. Share of the response option on the y-axis (%).

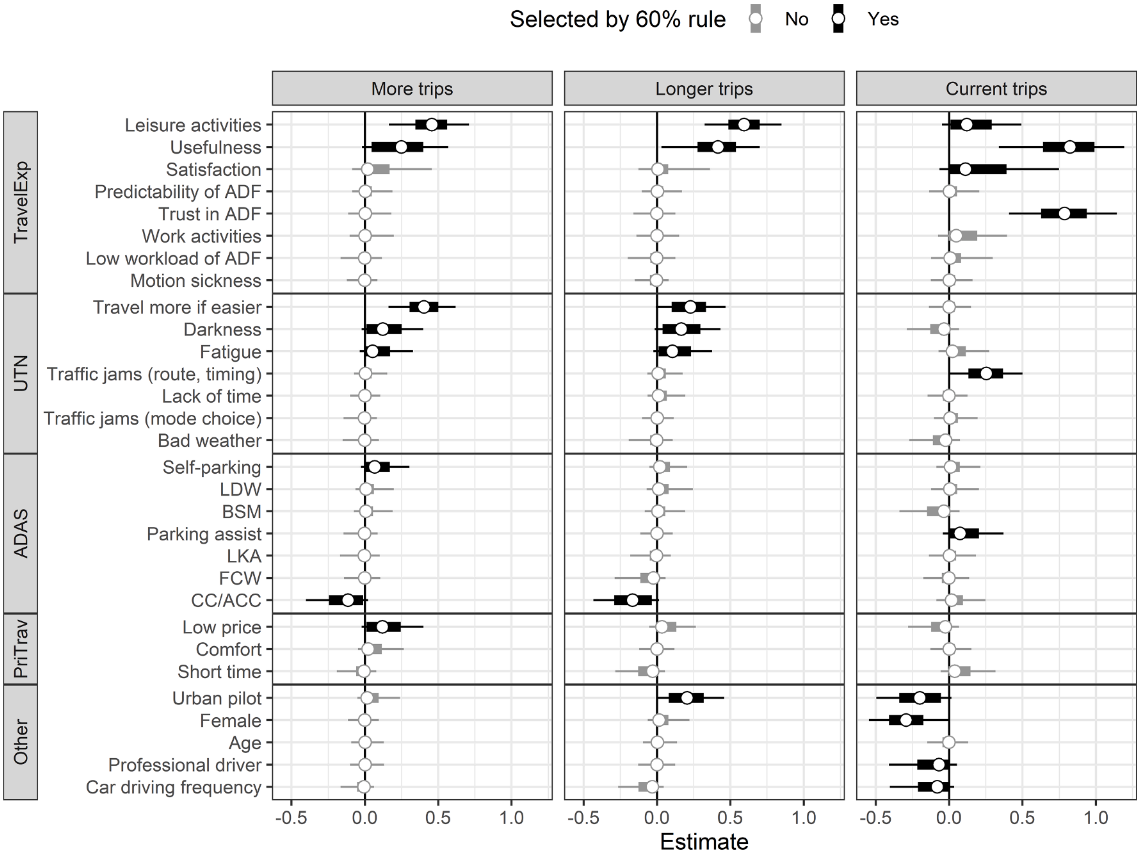

Fig. 2. Posterior predictive intervals for the coefficients of predictors based on the Bayesian cumulative ordinal regression models with regularised horseshoe priors. 60% (thick bars) and 95% (thin bars) credibility intervals shown. Median of the posterior distribution shown as dots. Predictors selected for the sparse model by projective prediction are shown in black, unselected in grey. Predictors are categorised to travel experience (TravelExp), unmet travel needs (UTN), priorities in travelling (PriTrav), experience with ADAS systems (ADAS), and other.

Table 6
Prediction accuracy of the unpenalised, penalised and relaxed models. Expected log pointwise predictive densities (ELPD) (ELPD) and their difference compared to the relaxed models.

Impact variable	Model	ELPD	ELPD Difference
More trips	Relaxed model	−524.0 (9.6)	N/A
	Penalised model	−532.8 (8.2)	−8.9 (3.0)
	Unpenalised model	−542.7 (11.0)	−18.7 (4.7)
Longer trips	Relaxed model	−535.5 (8.9)	N/A
	Penalised model	−543.1 (7.7)	−7.6 (2.5)
	Unpenalised model	−552.9 (10.7)	−17.4 (4.9)
Current trips	Relaxed model	−335.6 (17.0)	N/A
	Penalised model	−343.7 (16.1)	−8.1 (3.7)
	Unpenalised model	−351.3 (17.9)	−15.7 (4.3)

majority expected to use AVs only on their current trips. In general, this is in line with existing findings, which have generally predicted that vehicle automation will increase car travel (Hardman, 2021; Kröger et al., 2019; Lehtonen, Wörle, et al., 2021; Sonnleitner et al., 2021; Soteropoulos et al., 2019; Wadud et al., 2016). The responses also suggest that it might be easier to imagine taking longer trips by AV than completely new trips. New trips and the activities associated with these would require reallocating the daily time budget more dramatically than just extending the duration of existing trips.

To identify the main contributors to travelling more, the most predictive subsets of the variables were identified with cumulative ordinal regressions with shrinkage priors. The resulting penalised models achieved a better prediction accuracy than the unpenalised models, meaning that penalisation was able to reduce the overfitting due to noise in the data. The resulting sparse models (i.e., with fewer terms than originally) increased the explainability of the phenomena compared to models with all the terms. They could also guide future data-collection efforts by helping select which questions should be included in the questionnaires.

AVs could enable repurposing the driving time and reduce the unwanted efforts of driving, which could motivate travelling more once AVs become available. In line with that, willingness to perform *Leisure activities* during AD was the strongest positive predictor for making more trips or longer trips by AV. This suggests that the possibility to engage in “fun” or “relaxing” non-driving related activities during AD can be an important motivation for travelling more by AV. Positive responses to the question *Travel more if easier* were also associated with making more trips or longer trips. Also experiencing *Darkness* or *Fatigue* as barriers to driving were associated with travelling more by AV. This suggests that increased travel by AV is partly motivated by having some unmet travel needs, which AVs could address by making travelling easier. *Leisure activities* and addressing unmet travel needs could be interpreted to reflect the perceived usefulness of AVs. *Usefulness* was indeed positively associated with travelling more or longer trips.

Usefulness was the strongest predictor of willingness to use AVs on current trips. *Leisure activities* was also a positive predictor on current trips, but the association was weaker than with making more or longer trips. For current trips, *Trust in ADF* (indicating that the driver feels safe and comfortable letting the AV drive) and *Satisfaction* (indicating that the driver liked using the ADF) increased willingness to use AVs on current trips, but not making more or longer trips. Willingness to use AV on current trips was also positively associated with experiencing that traffic jams affect route choice and timing of the trips and using parking assist systems. It is possible that traffic jams and the use of parking assist systems are both linked to the need to drive in congested urban environments, where AVs may be seen as a way to cope with the unwanted effort of driving in congested traffic (Beirão & Sarsfield Cabral, 2007; Higgins et al., 2018; Payre et al., 2014).

Interestingly, *Work activities* was not included in the most predictive subsets. This is in line with previous findings that travellers look forward to engaging in various activities during AD, but that productive use of travel time for working is not among the most desired activities (Nordhoff et al., 2020; Singleton, 2019).

Previous research has suggested that the possibility for productive use of travel time during commutes could motivate relocating further away (Moore et al., 2020; Nielsen & Haustein, 2018). At first sight, not finding a link between *Work activities* and longer trips seems contradictory to this. On the other hand, the answers to the current questionnaire may reflect more the desires of the respondents rather than what they would actually do. That is, respondents may look forward to performing work activities during their current commutes, but they would not want to prolong their commutes. However, if they faced a decision to live further away and possibly pay less for housing, AVs could be the trade-off between longer commutes and better housing. More elaborated modelling is needed to understand the complexity of mobility effects (e.g., Moore et al., 2020).

The identified predictors can be compared against the technology acceptance models, which have suggested that the perceived

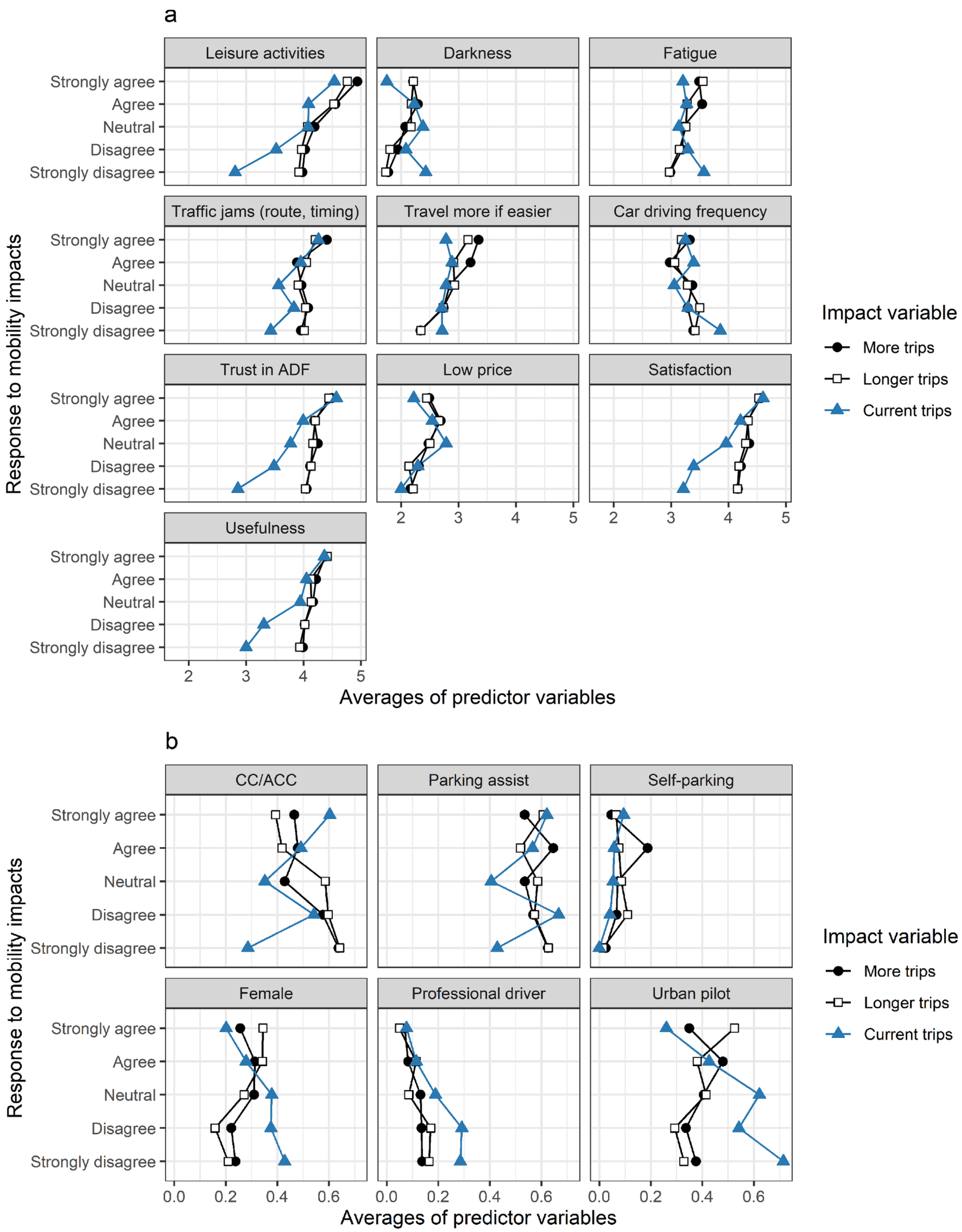

Fig. 3. Average values of predictor variables by responses to mobility impact questions. a) Non-binary predictor variables. b) Binary predictor variables.

usefulness and the perceived ease of use are the main determinants for intention to use a system together with trust in the system (Davis et al., 1989; Kolarova & Cherchi, 2021; Nordhoff et al., 2020; Zhang et al., 2019). In the current study, perceived usefulness appears to be the main predictor for using AVs on current trips and travelling more with them. However, to be used in the first place on current trips, AVs must also be trusted and experienced positively, but these may not be as important determinants for travelling more by AV. Future research could also investigate the role of hedonic motivations (i.e., enjoyment and fun) (Nordhoff et al., 2020; Venkatesh et al.,

2003) for travelling more by AV compared to using AVs on the current trips.

In addition to the predictors related to the travel experience, there were also others. Participants at the urban pilot sites were less willing to use the system on their current trips, but more willing to travel longer trips with the system. It is likely that urban ADFs need to request takeovers more often than motorway ADFs. This may decrease willingness to use the system on shorter, daily trips. Professional drivers and frequent car drivers were less willing to use the AVs on current trips. Possibly, professional drivers have a more realistic understanding of the system's limitations, which could reduce their willingness to use the system. Frequent car driving can be associated with enjoying car driving or less multimodality (Lehtonen, Malin, et al., 2021). Females were less willing to use the system on current trips, which is in line with many other studies (Liljamo et al., 2018; Nordhoff et al., 2020), but interestingly there was no association for more or longer trips.

Interestingly, the more experienced drivers were with *CC/ACC*, the more sceptical they tended to be about using an AV to make more or longer trips. Possibly, those who drive a lot are more experienced with CC/ACC, but because they already drive a lot they are less willing to drive more. In contrast, experience with *Self-parking* had a positive association but only for more trips.

Regarding travel priorities, it could be speculated that participants who prioritised *Comfort* or *Short time* could see AVs more positively, as AVs reduce the effort of driving and free up time for other activities. However, there was no associations with the variables. Only prioritising *Low price* was positively associated with willingness to travel more trips — an association that would need further study to be interpreted.

The current study was novel in that the participants experienced AVs in real traffic. However, the experience was still different from ordinary use in many ways: The drivers were travelling on prespecified routes, and because the trips were not part of their daily routine they probably did not try to use the travel time as they would if they were, for example, taking their normal commute. This may have influenced their experience.

The studied pilot participants were more willing to use a conditionally automated car for their current trips than European participants in a general public survey (81% vs. 53% agreeing that they would use a conditionally automated car on current trips) (Nordhoff et al., 2020). Experiencing AD has been shown to increase its acceptance (Xu et al., 2018), but the difference between the current sample the general public survey is so large that the experience alone may not explain it. The pilot sites often recruited the participants from among their own employees or via their networks, which may have resulted in a sample that was more enthusiastic than the general public toward AD. Company employees may be unwilling to express their critical views toward the tested system (Radun et al., 2019). Therefore, the system related ratings can be biased toward positive values. The same bias is less likely to apply to items related to current personal mobility or willingness to change travel behaviour due to AVs. If the items related to the experience with the system, such as *Usefulness, Satisfaction,* and *Trust,* are more biased toward positive ratings than others are, it is possible that the current results underestimate their contribution to the impact variables.

4.1. Conclusions

The current study found that conditionally automated cars have substantial potential to increase travelling by car once they become available. Increased car travel may pose a challenge to the sustainability of the future transport system. When promoting the uptake of private AVs, for example because of the expected safety benefits, it is important to remember that this may also mean promoting increased car travel.

We identified contributors for undertaking more or longer trips by AV and for using AVs on current trips. Repurposing the travel time for leisure activities or addressing currently unmet travel needs were the main contributors to travelling more by AV. These can be interpreted to reflect the perceived usefulness of AVs. For using the AVs on current trips, also trust and satisfaction with the system emerged as relevant. In addition, AVs can be seen as a way to cope with traffic jams. The results suggest that one way to limit the growth of traffic with private AVs could be to address currently unmet travel needs with alternative, potentially more sustainable travel modes, such as shared AVs, automated public transport, or e-bikes.

CRediT authorship contribution statement

Esko Lehtonen: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Fanny Malin:** Conceptualization, Writing – review & editing. **Tyron Louw:** Data curation, Writing – review & editing. **Yee Mun Lee:** Data curation, Writing – review & editing. **Teemu Itkonen:** . **Satu Innamaa:** Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2022.06.014.

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