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Travel experience matters: Expected personal mobility impacts after simulated L3/L4 automated driving

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Abstract

Automated vehicles (AVs) are expected to change personal mobility in the near future. Most studies on the mobility impacts of AVs focus on fully automated (SAE L5) vehicles, but the gradual development of the technology will probably bring AVs with more limited capabilities to begin with. This stated-preference study focused on the potential mobility impacts of conditionally automated (L3) and highly automated cars (L4). We investigated personal mobility impacts among 59 participants who experienced automated driving repeatedly in a driving simulator. Half of them drove with an L3 and half with an L4 motorway function. After the first and final drive they answered questions on their travel experience and how automated vehicles could change their mobility. After the drives, participants in both groups were willing to accept 30–50% longer travel times for a 30 min trip if they did not need to drive the whole trip themselves. This translates into savings of around 30% for the perceived value of travel time on routes where automation is available. There were no statistically significant differences between L3 and L4 in the accepted travel times. Most participants did not expect to make more trips with automated cars, but around half of them anticipated making longer trips. The amount of car travel may increase more with L4 than with L3 automation, possibly due somewhat to changes in the experienced travel quality. The results suggest that the mobility impacts of automated driving may increase with a higher level of automation.

Keywords Automated vehicles · Travel behaviour · Travel demand · Travel quality · Value of travel time savings · Driving simulator

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Introduction

Automated driving allows drivers to spend their travel time for other purposes than driving, such as relaxing, socialising or working, and it can also make travelling more comfortable, for instance in heavy traffic (Milakis et al. 2017; Singleton 2019). These changes in the *quality of travel* can induce changes in *travel patterns* and *overall amount of travel* (Kuisma et al. 2019): people may choose travelling by car over other modes more often, and even start making additional trips and select destinations farther away.

The main theoretical construct to understand and model these changes is the perceived *value of travel time* (VTT). VTT is the difference between the opportunity value of travel time (the utility which could be produced if the time were spent for other activities) and the value created while travelling (DeSerpa 1971; Kouwenhoven and de Jong 2018). The possibility to engage in other activities (such as working, relaxing, exercising) during the travel time increases the value created while travelling, resulting in net VTT savings (Kouwenhoven and de Jong 2018; Le et al. 2020; Wardman et al. 2020). The digital revolution has enabled the productive use of travel time in an unprecedented manner. It has already influenced VTT among public transport passengers, who can easily engage in other activities (Wardman et al. 2020). Automated driving could revolutionise the productive use of car travel time.

Besides other activities, VTT savings can also arise from the positive utility of the travel itself (e.g., allowing time off from other duties; Singleton 2019). It is also influenced by other qualitative factors such as the reliability of travel and the purpose of the journey (Small 2012). The subjective nature of VTT can be emphasised by using the term perceived VTT. In the following, perceived VTT and VTT are used interchangeably.

Estimates for VTT savings in AVs vary. Based on stated preferences, Kolarova et al. (2019) derived 41% savings in VTT for fully autonomous vehicles compared to manually driven cars for commuting trips but none for other trips. In modelling studies, a wide range of values have been used; for example, Kröger et al. (2019) used a 25% reduction in VTT with fully autonomous vehicles, and Wadud et al. (2016) used values ranging from 5–80% depending on the level of automation.

With lower VTT (that is, higher savings) in AVs, users may be willing to travel longer distances and even undertake new kinds of trips. Simulations focusing on the impact of AVs have linked reduced VTT to increased car use, especially when AVs are personal rather than shared (Soteropoulos et al. 2019). Lower VTT with automated driving has also been linked to decisions to relocate and accept longer distances between home and work (Moore et al. 2020). VTT, together with the direct monetary cost of travel, can be used to determine the *generalised costs* of travel (Litman 2016). Generalised costs provide a way to compare and predict mode choices between very different travel modes. Travel time and its reliability account for about half of the generalised costs (Small 2012). Understanding the potential changes in VTT due to automated driving is thus essential for understanding the impact of automated driving on the sustainability of the transport system, including number of crashes, congestion, emissions and implications for land use (Milakis et al. 2017; Spence et al. 2020).

So far, research on the personal mobility impacts of automated driving has focused primarily on fully automated vehicles which can perform dynamic driving tasks autonomously in all conditions (L5) (SAE 2018). However, from the user perspective, even lower levels of automation can change the travel experience in a way which may reduce VTT (Hardman 2020; Várhelyi et al. 2020). Nevertheless, it is likely that personal mobility effects are going to be greater for higher levels of automation compared with lower. An especially large difference can be expected between conditionally automated (L3) and highly automated (L4) vehicles. Both types of AVs can function within their limited operational design domain (ODD).

L3 AVs require a human driver as fallback, meaning that the driver must be ready to take back control swiftly when asked (e.g., if the road markings are not visible). L4 AVs allow driver more time to take back control when transitioning from automated driving to manual driving (e.g., when exiting a motorway). Hence, the driver can focus more closely on non-driving-related activities when using an L4 as opposed to an L3 AV.

The key challenge when studying the mobility impacts of AVs is that AVs are not yet widely available. Therefore, it is not possible to investigate the realised preferences of travel behaviour as a response to automated vehicles. Stated-preference studies exploring hypothetical choices are a valuable method for exploring the mobility impacts of AVs not yet in use (e.g. Kolarova et al. 2019). However, studies generally must resort to describing AVs either textually or using videos, which may not fully convey the experience of automated driving, making it harder to imagine how they could fit as a part of personal mobility.

A particular issue is trust in automated driving. Trust influences reliance and the intention to use automated vehicles (Lee and See 2004; Nordhoff et al. 2018). Travellers who have a low intention to use AVs are also less likely to expect them to change their personal mobility (Lehtonen et al. 2021). Without direct experience the trust is societal, based on expectations of society's ability to ensure the trustworthiness of the technology—or relational, based on experiences with other technologies such as computers (Lee and Kolodge 2020). Simulators could thus be a way to provide an experience of the automation and build experiential trust in the system.

Metz, Wörle, Hanig, Schmitt, Lutz & Neukum (2021) used a simulator to study the driving experience and behavioural adaptation in L3 and L4 automated driving over an extended period of time. The results suggested that both automation types were perceived as comfortable and safe, but L4 automation was rated better than L3. The ratings also improved with repeated usage. Also, the time spent engaged in non-driving-related activities and looking away from the centre of the road increased. The positive travel experience and time spent engaged in other activities suggest that L3 and L4 AVs would reduce the VTT, and that the effects could be larger with L4 than L3 and increase with repeated usage. The current study analysed mobility impacts based on the data collected in the experiment.

Objectives

In this study, we compared the potential mobility impacts of L3 and L4 automated driving with stated-preference data from participants having driven an L3 or L4 AV in a driving simulator six times on six different occasions.

The evaluation focused on three key variables regarding potential mobility impacts: (1) The first impact was related to the additional time the participants would be willing to spend travelling if they did not need to drive themselves the whole time. The logic is that if they perceive a longer time to be acceptable, then the perceived value of travel time must be lower due to the automation. Additional time was requested for 30 min trips in two scenarios, one to cover a longer route and the other due to rush hour congestion. VTT savings were expected to be linked to willingness to travel more often by car and over longer distances. Therefore, we also asked whether the participants would (2) increase the number of trips travelled and (3) travel longer distances.

The potential mobility impacts were also compared to the travel experience. We expected that the possible differences in mobility impacts between the systems and/or sessions would be explainable by differences in travel quality.

Methods

Automated driving function implementations

Two implementations of an automated driving function (ADF) for motorways were set up in the driving simulator, one at L3 and the other at L4 in accordance with the motorway functionality defined within the L3Pilot project (Metz et al. 2019).

Both L3 and L4 ADFs executed longitudinal and lateral vehicle control automatically over a speed range of 0–130 km/h. The ADFs followed the posted speed limit and adapted to the speed of the surrounding traffic. When approaching a slower lead vehicle, the ADFs executed an overtaking manoeuvre automatically. Both ADFs had system boundaries (i.e. ODD), and if these were not met a request to intervene was issued to the driver. The request to intervene consisted of a gradual sequence of visual warnings on the tachometer display (see Fig. 1) along with acoustic warning tones. The human–machine interface of the ADFs was designed to be very basic and simple. In the L4 condition, a take-over notification was issued stating that the automated driving would end soon (in 45 s). The urgent take-over warning was issued next, telling the driver to take over immediately (in 15 s). If the driver did not respond, the screen switched to minimal risk manoeuvre (MRM) mode, stating that the vehicle would now break until standstill. In the L3 condition, the urgent take-over warning was presented without first giving the take-over notification. If the driver did not respond, the ADF initiated an MRM and the vehicle came to a stop. The differences between the L3 and L4 ADFs are summarised in Table 1.

Study design

The basic idea of the study design was to expose a sample of regular, non-professional drivers to a simulated ADF on several occasions to capture potential changes in usage and experience of the tested ADF. All drives, including the familiarisation drive, were conducted on a three-lane motorway with varying speed limits. Environmental conditions such

Fig. 1 High fidelity driving simulator (left) and visual request to intervene on the tachometer display (right)

Table 1 Differences between the L3 and L4 ADF

	L3 ADF	L4 ADF
System boundaries	Exits and entrances to motorways Construction sites Heavy rain Missing lane markings	Exits and entrances to motorways Construction sites Heavy rain
Take-over time	15 s	45 s
Take-over request	Two stages: Urgent take-over warning and MRM	Three stages: Take-over notification, urgent take-over warning and MRM
Instruction	Drivers are instructed that they are allowed to withdraw from the driving task and engage in other activities. However, they are obligated to respond to requests to intervene and they are responsible for the safety of the drive	Drivers are instructed that they are allowed to withdraw from the driving task and engage in other activities. If they do not respond to a request to intervene, the ADF will execute a safe stop. The ADF is responsible for the drive

as weather, road conditions, traffic density and infrastructure varied within and between the drives. The aim was to create as naturalistic a driving environment as possible. Drivers were instructed that they were allowed to perform other activities but might be asked to intervene (see Table 1 for specific instructions).

Driving simulator

The study was conducted in a high-fidelity moving-base driving simulator at the WIVW GmbH facilities. The simulator consists of a mock-up of a production type BMW 520i placed in a dome (Fig. 1). The driving environment is projected inside the dome by three LCD projectors that provide a 240 ° surround view. The dome is fixed on a motion system consisting of six electro-pneumatic actuators that display the driving motion. The simulator runs with the simulation software Silab® (WIVW GmbH, Veitshöchheim).

Procedure

Every driver experienced six driving sessions on six different days. The drives in sessions 1, 2, 4 and 6 took about 30 min, and in sessions 3 and 5 around 90 min. Before and after each drive, the German translation of the L3Pilot pilot site questionnaire (Metz et al. 2019) was administered either as a full questionnaire after sessions 1 and 6 or in a shorter format.

In the first driving session, all drivers gave their informed consent, completed the full L3Pilot pre-questionnaire and received a general description of the relevant ADF. They learned that the system was able to operate within certain boundaries and that if these boundaries were reached, the driver would have to take over. They then completed a familiarisation drive, during which they became acquainted with handling the ADF, practised control take-over situations and performed a minimal risk manoeuvre. Drivers were guided through the familiarisation drive and it was ensured that they understood the ADF. After the 10 min familiarisation drive, the drivers were told that during the test drives they were free to use the ADF as they liked. They could, for example, activate or deactivate it whenever they wished, and they were free to engage in non-driving-related activities during the drives. The drivers were instructed to bring to the experimental sessions whatever they would like to engage in during an automated drive (for a more detailed analysis of non-driving related tasks, refer to Metz et al. 2019).

The drivers were exposed to 2–5 take-over situations per drive (a request to intervene was issued and the driver had to take back control of the vehicle and resolve the situation). Both ADFs were implemented as “mature” systems with no automation failures happening during the drives.

User questionnaire

The current study analysed the mobility-related questions included in the long version of the L3Pilot pilot site questionnaire administered after the first and sixth drives. The questions were aligned with the L3Pilot mobility impact evaluation framework (Innamaa et al. 2020; Kuisma et al. 2019). The framework assesses potential impacts on personal mobility through three main dimensions: travel quality, travel patterns and amount of travel. The three main dimensions were further divided into sub-dimensions as shown in Table 2.

Table 2 User questionnaire items used in the current study. Also showing dimensions of the L3Pilot mobility model and the response scale

Dimension	Sub-dimension	Question	Scale
Amount of travel	Additional travel time accepted	You have a trip that takes 30 min of driving. There is an alternative route, which is somewhat longer but in which a [L3/L4] self-driving system would be available. How much additional time would you be willing to accept for this alternative route, where the car could drive by itself and you could engage in other activities?	Number of minutes
		Imagine that you have a partly self-driving car which is able to drive by itself in congestion. You have a trip that takes 30 min of driving. You have scheduled it to avoid the peak of congestion. How much additional time would you be willing to accept for the duration of this trip if the car could drive by itself and you could engage in other activities?	
	Number of journeys	I would make MORE trips if I had the function in my car	5-point Likert scale: Strongly disagree, Disagree, Neutral, Agree, Strongly agree
	Trip length	I would select destinations further away if I had the function in my car	
Travel quality	Secondary task engagement	I would use the time the system was active to do other activities	
	Feeling of comfort	Driving with the system active was comfortable	
	Feeling of safety	I felt safe when driving with the system active	
	User confidence	The system worked as it should	
	User stress	Driving with this system was stressful	
		Driving with this system was difficult	
		Driving with this system was demanding	

In the present study, the focus was on the amount of travel. Therefore, we analysed the questions on the additional time accepted with automation to determine VTT savings, and expected changes in the length of and number of journeys. Changes in travel quality were compared with changes in the amount of travel. The questions used in the assessment are given in Table 2.

Participants

Sixty-one drivers were recruited from the WIVW driver panel. All drivers had completed extensive driving simulator training (Hoffmann and Buld 2006) before participating in the study. The training is done to avoid learning effects during the experiments and to screen out drivers who are prone to simulator sickness.

Two L3 participants were removed from the analysis because they had not fully completed questionnaires after both the first and the sixth drives, resulting in 59 participants. The sample was made up of adults (average age = 37.93, SD = 11.73). Most of them were employed (68%) or students (29%); 78% of them had a car available for their use 'nearly always' and 14% 'sometimes'; 75% had more than 10 years' driving experience, 24% had 2–10 years, and one participant (2%) had 1–2 years; 44% used cruise control or adaptive cruise-control while driving.

Analysis

Automation types (L3 vs L4) were compared in terms of additional travel time accepted and willingness to make more or longer trips with an automated car. The effect of the session (1st vs 6th) on the three metrics above was similarly investigated. The travel quality score was calculated to investigate whether the differences between automation types and sessions could be linked to changes in travel quality. Additional travel times were also translated into VTT savings. R version 4.0.2 was used to perform the tests. An "ordinal" package was used for CLMMs (Christensen 2019). Criterion $p < 0.05$ was used as the threshold for statistical significance in all tests.

Additional travel time

We tested whether the participants were willing to accept additional travel time due to automation. A one-sided Wilcox signed rank test was used to ascertain that additional time values were greater than zero, which was the lowest possible value. We then compared the additional times between the first and sixth sessions within the automation levels using paired Wilcox signed rank tests. Non-paired Wilcox signed rank tests were used to test if the additional times given were different for the automation levels (L3 vs L4). The analysis was performed separately for the first and sixth sessions. A non-parametric test was used because the linear parametric model would give misleading results for zero truncated distributions.

Number of trips and trip length

The responses to questions regarding changes in the number of trips (I would make MORE trips if I had the function in my car) and their length (I would select destinations further away if I had the function in my car) were investigated. Because the responses were given on a five-step Likert scale, the differences between automation types for the sixth session were also tested with non-paired Wilcox signed rank tests.

In addition, Cumulative Link Mixed Models (CLMM) were used to analyse the effects of session and automation type within the same model. CLMMs are suitable for ordinal data with repeated measures. The participant was included as a random effect, and automation type (L3 vs L4), session (1st vs 6th) and their interaction as fixed effects.

Travel quality

Travel quality scores were calculated as an average of the travel quality questions. Before averaging, the responses were recoded as 'Strongly disagree' = 1, 'Disagree' = 2, 'Neutral' = 3, 'Agree' = 4 and 'Strongly agree' = 5. Negatively stated user stress questions were first reversed, so that higher coded values would represent positive evaluations. There were three missing or "I don't know" answers from three participants to the questions "The system worked as it should", "Driving with the system was comfortable", and "I would use the time the system was active to do other activities". These three responses were removed from the analysis of the specific variables, but otherwise the data from the participants was retained.

The differences in travel quality between automation types and sessions were examined using non-parametric tests; as with the additional travel times, the scale of the score was limited to between 1 and 5, and the values were concentrated at the upper end of the scale.

The correlation between travel quality score and additional time accepted, number of trips and their length was calculated focusing on the sixth drive using Spearman rank correlations. CLMMs were also used to investigate whether the travel quality score could explain the variability between sessions and automation types in the questions pertaining to more trips and trip length. To do so, models with a travel quality predictor were compared to the aforementioned models with automation type and session predictors in terms of Bayesian Information Criteria (BIC) and Nagelkerke Pseudo R^2.

VTT savings

VTT savings were estimated based on the additional time accepted. It was assumed that the total cost of travel would be equal to the product of the baseline trip duration driven manually (T_{MV}) and the VTT when driving manually (VTT_{MV}). Assuming that respondents aim to keep the overall costs the same, this equals the product of automated driven time ($T_{AV} = T_{MV}$ + additional travel time accepted) and the VTT in automated driving (VTT_{AV}). Consequently, the ratio between accepted travel times directly reflects a change in the value of travel time (Eq. 1). VTT savings (VTTS) due to automated driving can then be calculated (Eq. 2). This assumption is of course only an approximation. It does not properly consider the other costs of travel and does not consider the traveller's limited time budget (Kouwenhoven and de Jong 2018), which are outside the scope of this paper.

$$T_{MV} VTT_{MV} = T_{AV} VTT_{AV} \Leftrightarrow \frac{VTT_{AV}}{VTT_{MV}} = \frac{T_{MV}}{T_{AV}} = \frac{T_{MV}}{T_{MV} + additional\ travel\ time\ accepted} \tag{1}$$

$$VTT_{AV} = (1 - VTTS) * VTT_{MV} \Leftrightarrow 1 - VTTS = \frac{VTT_{AV}}{VTT_{MV}} \Leftrightarrow VTTS = 1 - \frac{T_{MV}}{T_{MV} + additional\,travel\,time\,accepted} \tag{2}$$

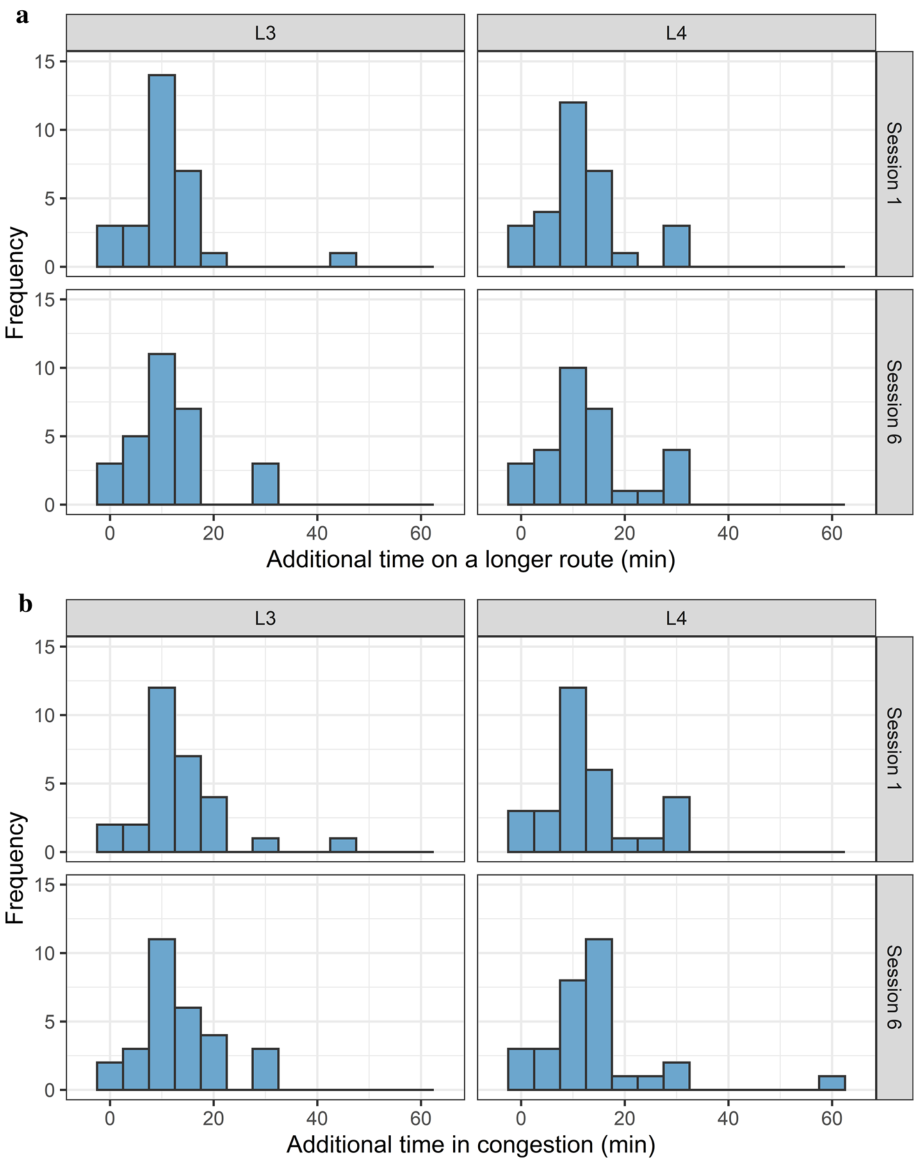

Fig. 2 Accepted additional time for a 30 min trip for a) an alternative longer route and b) when driving in rush-hour congestion vs. leaving at other times, if the vehicle were to drive in automated mode most of the time

Results

Additional travel time

Respondents were willing to accept additional travel time if the car could drive by itself and they could engage in other activities. Figure 2a shows the additional times accepted in the scenario with a longer alternative route where automation would be available, and Fig. 2b when automation could be used to travel during rush hour compared to making a trip at another, less congested time. The median additional time accepted for a trip lasting 30 min was 10 min in both scenarios and with both automation types after the first drive. After the sixth drive, the medians were unaffected for L3 (10 min). For L4, the median for the congestion scenario increased up to 15 min but remained the same (10 min) in the longer route scenario. The additional times accepted were statistically significantly greater than zero (Table 3). There were no statistically significant differences between automation types and sessions.

It can be argued that the time values given after the sixth drive represent participants' best estimates of the maximum additional times accepted. Based on this, VTT savings can be estimated to be 25–33% for both automation types and scenarios.

Number of trips

In the sixth session, 17% of the L3 group and 30% of the L4 group expected to start making more trips with automation (Fig. 3). The difference between L3 and L4 in the sixth session was statistically significant when tested with a non-paired Wilcoxon signed rank test ($W=281$, $p=0.026$). Looking at Fig. 3, the participants started agreeing more with the statement over the drives. However, the ordinal regression model did not show significant effects (Table 4).

Table 3 Descriptive statistics for additional time. One-sided Wilcox test for the hypothesis that the durations are greater than zero

	Automation type	Session	Median	Bootstrapped 95% CI for median		M	SD	Additional time greater than zero	
				Lower	Upper			V	p
Additional time for alternative route	L3	1	10	10	12	11.3	8.09	351	<0.001
	L3	6	10	10	15	11.5	7.79	351	<0.001
	L4	1	10	10	15	11.8	7.82	378	<0.001
	L4	6	10	10	15	13.0	8.77	378	<0.001
Additional time in congestion	L3	1	10	10	15	13.5	8.65	378	<0.001
	L3	6	10	10	15	13.2	7.86	378	<0.001
	L4	1	10	10	15	13.1	8.61	378	<0.001
	L4	6	15	10	15	14.2	11.3	378	<0.001

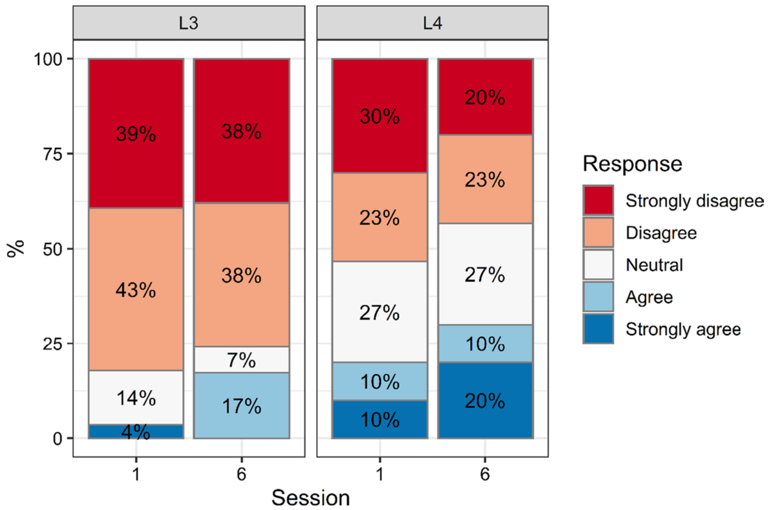

Fig. 3 Responses to the statement "I would make MORE trips if I had the function in my car"

Table 4 Coefficients of ordinal regression models for trip frequency and destination questions

Predicted variable	Predictor variables (fixed terms)	Estimate (SE)	Z	*p* value
Number of trips	L4 (ref. L3)	1.2704 (0.7418)	1.713	0.087
	Session 6 (ref. Session 1)	0.5184 (0.5404)	0.959	0.337
	L4 x Session 6	0.4204 (0.7433)	0.566	0.572
Number of trips	Travel quality score	1.601 (0.600)	2.668	0.008*
Trip length	L4 (ref. L3)	0.7667 (0.9230)	0.830	0.406
	Session 6 (ref. Session 1)	−0.1979 (0.5754)	−0.344	0.731
	L4 x Session 6	1.6758 (0.8065)	2.078	0.038*
Trip length	Travel quality score	1.3903 (0.5908)	2.353	0.019*

Statistically significant *p* values ($p < 0.05$) marked with *

Trip length

At the sixth session, 45% of the L3 group and 60% of the L4 group expected to make longer trips with automation (Fig. 4). The difference between L3 and L4 at the sixth session was statistically significant when tested with a non-paired Wilcoxon signed rank test (W = 268.5, $p = 0.016$). The ordinal regression model for the trip length had a statistically significant interaction term (Table 4). The L4 participants appeared to become more favourable toward the statement, while the L3 participants did not change their views.

Respondents agreed with making longer trips more often than with making more trips. The increase was statistically significant both in the first (non-paired Wilcoxon signed rank test, W = 2110.5, $p = 0.015$) and sixth sessions (W = 2073, $p = 0.027$) when the automation types were collapsed, but not if they were they were tested separately.

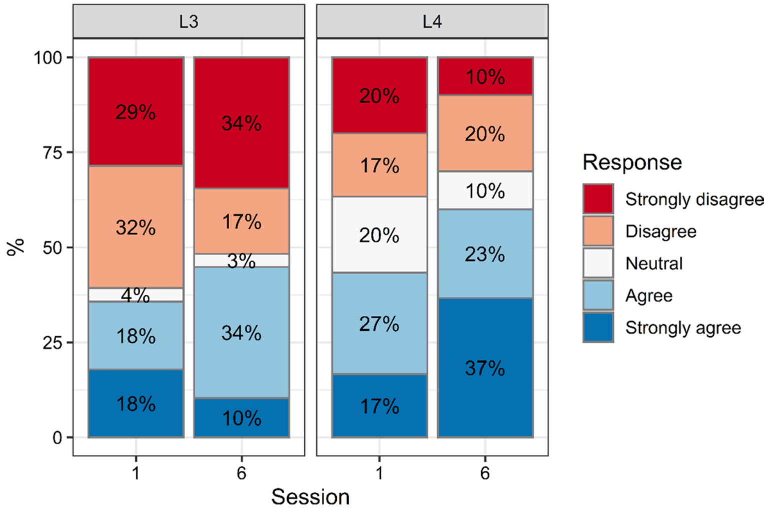

Fig. 4 Responses to the statement "I would select destinations further away if I had the function in my car"

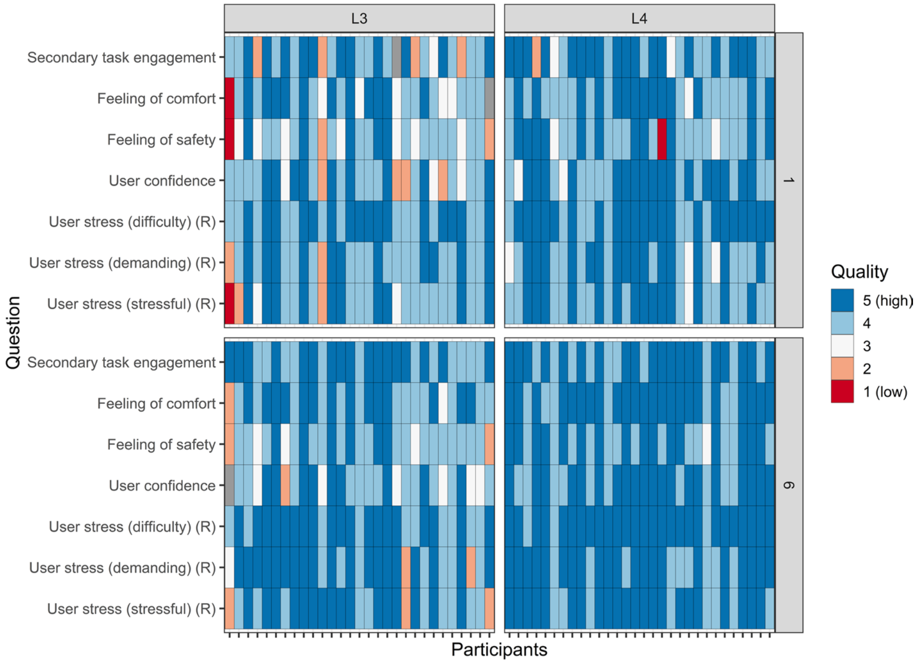

Fig. 5 Travel quality by question. Each column represents one participant. Higher values represent positive (e.g. higher comfort or lower stress) and lower negative quality (e.g. lower comfort or higher stress). Responses to the questions marked with R were reversed before coding. Three missing responses are shown in grey

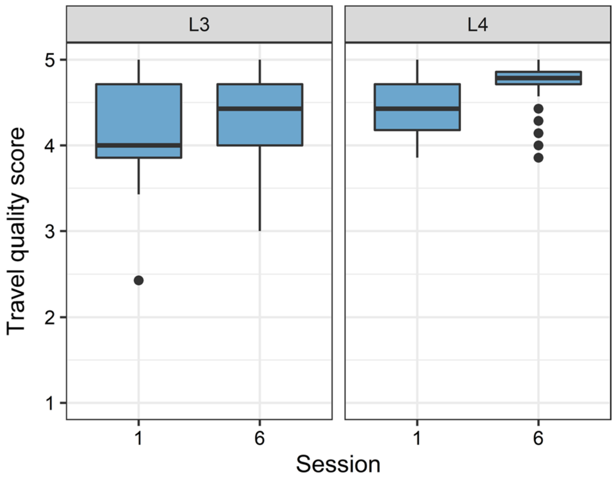

Fig. 6 Boxplots for the travel quality score by automation type (L3 vs L4) and driving session (1 vs 6)

Travel quality

Figure 5 summarises visually the responses to the travel quality questions. At the sixth session, all or an overwhelming majority of participants agreed that they would perform other activities while the system is active (100%), and that they would feel comfortable (97%), safe (90%) and confident about the functioning of the automation (88%). All or a majority of participants also disagreed that driving with automation would be demanding (95%), difficult (100%) or stressful (95%).

The travel quality score was calculated as an average of the recoded responses to the travel quality questions (Fig. 6). Travel quality increased from the first to the sixth sessions with both automation types (paired Wilcoxon signed rank test, L3: V = 53, $p = 0.010$; L4: V = 36, $p = 0.001$). L4 automation also had a higher travel quality than L3 both in the first (non-paired Wilcoxon signed rank test, W = 289, $p = 0.026$) and sixth sessions (W = 246, $p = 0.004$).

Spearman rank correlations between travel quality score and mobility questions were calculated using the data from the sixth session. The quality correlated only weakly with the additional travel time accepted (longer route: rho = 0.16, $p = 0.22$, congestion: rho = 0.12, $p = 0.37$). Correlations were stronger and statistically significant for the

Table 5 Comparison of the CLMM model with automation type x session fixed-term predictors and travel quality predictor for questions on trip frequency and destination

Predictor variable	Predictor variables (fixed terms)	Number of parameters	Log Lik	BIC	Nagelkerke Pseudo R^2
Number of trips	Automation type x Session	6	– 160.73	354.74	0.085
Number of trips	Travel quality	4	– 161.40	346.57	0.074
Trip length	Automation type x Session	7	– 163.41	360.09	0.096
Trip length	Travel quality	5	– 166.37	356.51	0.046

Nagelkerke Pseudo R^2s are calculated relative to the Intercept only model question regarding making more trips (rho = 0.38, $p = 0.003$) and making longer trips (rho = 0.30, $p = 0.020$).

CLMMs were used to investigate if the travel quality score could explain the responses given to the number of trips and trip length questions. For both questions, the effect of travel quality score was positive and statistically significant (Table 4). Models with automation type x session predictors were compared to the models with the travel quality score predictor. The Bayesian Information Criterion (BIC) suggests that the travel quality score could be a more parsimonious predictor than automation type and session (Table 5).

Discussion

The current study investigated the potential impact of L3 and L4 automated driving on personal mobility with a stated-preferences questionnaire among participants having experienced automated driving in a simulator. The questionnaires were filled in after the first drive, then repeated after the sixth drive to understand whether repeated experience influences the assessment.

The participants were willing to accept additional travel time if they could use automated vehicles and would not need to focus on driving. Additional travel times accepted were similar both in the scenario with a longer alternative route where automation would be available, and when automation could be used to travel during rush hour compared to making a trip at another, less congested time. After experiencing automated driving over six drives, the median additional time accepted was 10 min for L3 in both scenarios for a 30 min trip. For L4 automation, the additional time was likewise 10 min for the alternative route and 15 min for the congestion scenario. There were no statistically significant differences between the automation types and the first and sixth sessions.

The 95% confidence interval for the median additional time accepted was 10–15 min on the sixth drive for both automation types and scenarios. Accepted additional times translate into a 25–33% decrease in VTT due to automation. The result agrees with existing studies which have suggested or presumed that VTT drops with fully autonomous vehicles (Kolarova et al. 2019; Kröger et al. 2019; Soteropoulos et al. 2019). When answering the question, the participants did not have to consider what they could have done during the additional time if they had not travelled (the opportunity value) and if they had that time available. They also may not have fully considered the monetary costs of accepting additional travel times. Therefore, the accepted additional times should be treated as optimistic upper bound values. VTT savings could be somewhat lower once the vehicles are in real-life use.

The current results do not suggest that VTT savings due to automation were different between congested traffic and traffic in general. Aligned with that, a recent meta-analysis on non-automated driving did not suggest a difference in VTT between congested and free-flowing traffic (Wardman et al. 2016). Previous studies have suggested that VTT depends on the journey purpose and whether a trip is inter-urban or urban (Small 2012; Wardman et al. 2016). Further studies would be needed to explore whether VTT savings due to automation are similar for different types of trips.

Most participants did not think they would start making more trips with automation, but around half thought they would start travelling to destinations further away. Performing more trips may appear less plausible than making longer trips, because new trips could imply spending time at the trip destination also. Consequently, the more-trips question may have drawn greater attention to the issue of limited time budgets than to longer trips. Increases in the number and length of trips correspond with decreased VTT (Moore et al. 2020; Wardman et al. 2020).

L4 participants were more willing to perform more trips and longer trips than L3 participants, if we focus on the sixth session only (non-parametric non-paired Wilcoxon signed rank tests). CLMMs, in which both the first and the sixth session were included, gave a more conservative result. For the more-trips question, the null hypothesis could not be rejected, as the ordinal regression model found no significant effects. L4 participants were found to become more favourable with the idea of travelling longer trips in the sixth session, but for L3 participants there was no statistically significant change.

The questions pertaining to travel quality indicated that both automation types were experienced positively. A high quality of travel corresponds to an acceptance of additional travel time, indicating that participants would be willing to trade some time if they did not need to focus on driving.

L4 participants reported a higher quality of travel than L3 participants. The travel quality also improved from the first session to the sixth. This suggests that travel quality improves with increasing automation level (cf. Varhelyi et al. (2020), who found that L3 was rated higher than manual), and that simulator experience influences travel quality ratings. The results showed that travel quality was linked to a willingness to make more trips and longer trips, but no link to VTT savings was found. It is possible that the additional time questions were presented too much out of context. The participants were asked to imagine a scenario for which they were given a fairly detailed description. This may have reduced the influence of the simulator experience. Future studies could try to investigate the value of travel time by presenting the choice as part of the simulated drive.

Overall, the results suggest that travellers might be willing to make longer trips with AVs than with manually driven cars. The comparison of automation levels also suggests that with L4 automation, an increase in car travel may be greater than with L3, and that a higher travel quality in L4 vehicles can partially explain the effects. It is possible that L4 drivers see also other reasons to travel by highly automated AVs than the ability to engage in non-driving activities or increased comfort. For example, avoiding driving under the influence of alcohol has been suggested to be an important motive for using ride-hailing services (Dias et al. 2019). Some recreational travellers might prefer to risk driving while intoxicated by choosing an L4 AV, in which takeover times are long, over potentially expensive ride-hailing.

The main strength of the current study is that the stated-preference questions were posed after the participant had been exposed to simulated driving on a motorway over a longer term. This means that the participants had a richer experience of what automated driving would mean than if they had only read descriptions of automated driving or watched videos, which is the standard way of explaining automated driving in stated-preference studies. It can be questioned whether the results from a simulator study could ever transfer to a real-world setting, where the users of AVs need to trust that the system will not cause a crash with serious consequences. As a counterargument, it seems that drivers can quickly build trust in near-perfect automation to the extent that they become complacent and fail to respond when a system fails (e.g. Bahner 2008,Pipkorn et al. 2021). Future AVs on the market are likely to be ‘good enough’ to create trust among a significant proportion of potential users.

Nevertheless, the general limitations of stated-preference studies apply to the results. The impact of AVs on actual travel behaviour can differ from participants’ expectations. Travel behaviour is influenced by various factors of which even the travellers may not be fully aware. Thus, the results should be interpreted to indicate impact direction. Furthermore, the participants experienced automated driving on a motorway only; the benefit is that we can be fairly confident that our results are reliable for motorway trips, but caution should be exercised when generalising them to other environments.

Conclusions

Participants having experienced L3 or L4 automated driving in a simulator were willing to accept roughly 30–50% longer travel times in exchange for not having to drive themselves, suggesting that L3 and L4 automation may reduce VTT by around 30%. After repeated experience in a simulator, the L4 group were more favourable than the L3 group towards making more trips and selecting destinations further away once they had an automated vehicle. The differences in the mobility impacts between automation levels could be partially explained by the changes in experienced travel quality. The results suggest that L3 and L4 automation has potential in increasing the use of personal cars. Increasing the automation level may increase the travel quality and consequently also the mobility impacts.

Increased mobility by AVs can benefit individuals and society in many ways, but at the same time it may challenge the sustainability of the transport system. More energy is needed, and if it is produced with fossil fuels, more CO_2 emissions are produced. An increase in car kilometres may also make traffic congestion worse, increase the number of crashes, and produce more pollution (e.g. microplastics from car tyres) and noise. Travellers may shift form public transport and active travel to personal cars, further increasing the car dependence and making transition to multimodal transport system more difficult (Lehtonen et al. 2021). The potential adverse consequences of automation can be mitigated by limiting emissions by means of technology, regulation and taxation. The use of public transport and active travel should be prioritised whenever possible. Automated public transport (shared AVs) and electric micromobility could be a technological approach to increasing the attractiveness of these travel modes.

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Authors' contributions EL and FM contributed to the study conception. JW and BM provided the data from the experiment they had conducted. Data analysis was performed by EL. The first draft of the manuscript was written by EL and JW. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Code availability Analysis code is available from the first author on reasonable request.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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