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Exploring the usage of supervised driving automation in naturalistic conditions

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ABSTRACT

This study reports usage of supervised automation and driver attention from longitudinal naturalistic driving observations. Automation inexperienced drivers were provided with instrumented vehicles with adaptive cruise control (ACC) and lane keeping (LK) features (SAE level 2). Data was collected comparing one month of driving without support to two months where drivers were instructed to use automation as desired.

On highways, level 2 automation was used respectively 63% and 57% of the time by Tesla and BMW users, with peak usage during slow stop-and-go traffic (0–30 km/h) and higher speeds (>80 km/h). On roads with speed limits below 70 km/h, automation was used less than 8%, and use on urban roads was incidental rather than habitual. Automation usage increased with time in trip, but no clear time of day effects were found. Head pose data could not classify driver attention, and we recommend gaze tracking in future studies. Head pose deviation was selected as alternative indicator for monitoring activity. Comparing among forms of automation usage on the highway, head heading deviation was smallest during ACC use, but did not differ between automation and baseline manual driving. Head heading deviation during manual driving was smaller in the baseline than the experimental phase, which suggests that motives for manual highway driving may be attention related. Automation usage did not change much over the first 12 weeks of the experimental condition, and there were no longitudinal changes in head pose deviation.

1. Introduction

Supervised, or SAE Level 2 partial automation (SAE, 2021) is rapidly deployed in commercial cars. Current systems automate longitudinal control with adaptive cruise control (ACC) and support lateral control with lane keeping (LK).

While Level 2 automation is active, the driver has to supervise the automation, and intervene when needed to ensure safety.

However recent studies and accidents indicate that drivers occasionally use automation in unsuitable conditions, and are not always monitoring the environment sufficiently (Dutch Safety Board, 2019). Harms, Bingen, and Steffens (2020) found that drivers are not always aware of the abilities and limitations of current systems. Farah et al. (2021) also found that drivers over-estimated the operational design domain as defined by the vehicle manufacturer in an on-road study with a Tesla. Banks, Eriksson, O'Donoghue, and Stanton (2018) observed behaviours in a Tesla and noted that drivers occasionally missed notifications from the HMI, leading to mode confusion.

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1.1. Automation usage and experience

When and how drivers use the automation is motivated by their attitude towards the automation, perceived control over the situation and subjective norms (Madden, Ellen, & Ajzen, 1992; Venkatesh, Morris, Davis, & Davis, 2003; Nordhoff, van Arem, & Happee, 2016). The formation of attitudes is further described in models of trust (Lee & See, 2004; Hoff & Bashir, 2015) and depends on our mental model of the automation, and on the situation in which it is used. The outcome of this process can be inferred from automation usage, monitoring and the attention distribution between driving-related and secondary tasks (Meyer, Wiczorek, & Günzler, 2014).

As drivers' understanding of the automation develops with experience, so will their usage and monitoring behaviour (Sullivan, Flannagan, Pradhan, & Bao, 2016; Large, Burnett, Salanitri, Lawson, & Box, 2019). Experience can also lead to faster control transition routines Larsson, Kircher, and Andersson Hultgren (2014), lower perceived workload (Stapel, Mullakkal-Babu, & Happee, 2019) and larger secondary task uptake at especially slower driving speeds (Naujoks, Purucker, & Neukum, 2016).

The driver's perceived control is also influenced by their mental state. This may cause a change in usage as a driver gets fatigued (e.g. driving time) or sleepy (e.g. time of day). Automation use can also affect this state. It can initially improve alertness when well-rested (Ahlström et al., 2021), but can also degrade it over prolonged use through mental underload (Helton & Warm, 2008; Saxby, Matthews, Warm, & Hitchcock, 2013) and vigilance decrement (Greenlee, DeLucia, & Newton, 2018). Whether drowsiness promotes or discourages automation can therefore be highly situational.

1.2. Monitoring performance

Effective monitoring requires the driver to maintain situation awareness, which Endsley (1995) described as the perception of the environment, comprehension of its meaning and projection of this state into the future. Since perceptual capacity is limited, drivers need to divide and schedule attention over the available information sources (and distractions), see e.g. (Kahneman et al., 1973; Cohen, Aston-Jones, & Gilzenrat, 2004) for further theories of attention, cognitive control and error detection.

This scanning behaviour can be inferred from gaze or head movement (Lee et al., 2018) and can indicate distraction or attentional mismatches (Engström et al., 2013). Reduced on-road glance duration can impair hazard detection and takeover performance (Park, Gao, & Samuel, 2017; Glaser, Glaser, Green, Llaneras, & Meyer, 2017). Mental distraction, cognitive load, time pressure, fatigue and intoxication reduce the (especially horizontal) dispersion of visual scanning (Wang, Reimer, Dobres, & Mehler, 2014; Victor, Harbluk, & Engström, 2005; Rendon-Velez et al., 2016). Louw and Merat (2017) found that supervised driving automation increases horizontal gaze dispersion (as does driving on familiar roads (Young, Mackenzie, Davies, & Crundall, 2017)). They also found that gaze behaviour was similar to manual driving when drivers were made uncertain about the automation's autonomy. Similarly, Jamson, Merat, Carsten, and Lai (2013) found that driving automation increased time allocated to secondary tasks, but attention to the road was also adjusted depending on traffic.

1.3. Other naturalistic studies

While several studies were conducted in controlled or semi-controlled on-road conditions, only few investigated the use of and adaptation to automated driving in naturalistic settings. Beggiato, Pereira, Petzoldt, and Krems (2015) performed a longitudinal on-road study where they found that drivers developed their trust and functional understanding of ACC over ten drives while establishing a high acceptance within two drives. Morando, Victor, and Dozza (2019) investigated how SAE2 driving automation influences attention during 10 months of naturalistic manual and automated driving by 17 participants. They found longer on-road glances and lower percent eyes on road centre during automated driving (ACC and LK) compared to manual driving. The latter was attributed to a reduced task demand during automation use. Russel et al. (2018) conducted a naturalistic driving study with 120 participants driving vehicles equipped with adaptive cruise control and automated lane keeping for 4 weeks. They report effects of traffic stability, road type and weather conditions (no-precipitation vs precipitation) on automation use and found that drivers were performing secondary tasks 60% of the observed time regardless of automation use and found no difference in percentage eyes-off-road time, off-road glance duration or type of secondary task. Reaction times to the 'hold steering wheel'- requests did not change over the four weeks of use, but instances occurred in the first week where such requests were intentionally ignored to investigate the vehicle's response.

While these studies provide useful insights, the evolution of behaviour from manual to automated driving has mainly been examined for the first experience with automation, or lack observations of baseline manual driving prior to developing experience with automated driving.

1.4. Study objectives

In this study we report automation use and driver attention from longitudinal naturalistic driving observations conducted in the Netherlands. The study is unique in its inclusion of a one month manual driving baseline followed by a two month experimental phase with the same participants and vehicles where participants were allowed to use the vehicle's automation, enabling a within-subject analysis of behavioural adaptation over the first two months of automation usage.

We address the following research questions:

1. When and in which conditions do drivers use ACC and LK support?

2. Is driver attention different during manual driving compared to driving with supervised automation?
3. Do these behaviours change with automation experience?

We study automation use and driver visual attention allocation as a function of road type and driving speed. We study appropriate use relative to the operational design domain. We relate behaviour to time in trip and time of day, (which may show effects of fatigue and driver state); and time after first automation use (to examine behavioural adaptation with experience).

In order to perform these analyses, we explore to which extent the visual annotation of automation status and driver attention can be automated. We train a classifier to identify system icons in the instrument panel using video and to classify driver attention distributions among attentive regions and regions associated with non-driving tasks using head pose estimated from video. Both classifiers are trained and evaluated on manually annotated data from the naturalistic study.

This study focuses on within-subject effects of automation use. We do not analyse differences or similarities between vehicle types, since they were not driven by the same participants or in the same conditions. We do not generalize our findings or use them for theory testing because of the small number of participants.

2. Methods

2.1. Data description

In a collaborative project conducted by TNO, SWOV and the Dutch ministry of Infrastructure and Watermanagement, the RDW (Dutch Vehicle Authority) and RWS (Dutch Road Authority), recent passenger cars with SAE level 2 automation were equipped with instrumentation to observe the driver and the environment. Naturalistic driving data was collected by providing these vehicles for daily use to drivers having no prior experience with SAE level 2 automation. The naturalistic dataset is unique in that it includes one month of manual driving (baseline condition) followed by two months of use with automation under naturalistic driving conditions (experimental condition), allowing for a longitudinal within-subjects analysis of how automation use changes over time. The full dataset includes five vehicle types (BMW 540i, Tesla S, Mercedes E, Volkswagen Golf E, Audi A4 Avant) driven by 20 participants. However, automation usage information was successfully recovered from the CAN bus or video for for only two vehicle types (Tesla and BMW) and therefore 10 participants could be analysed for this paper. An overview of the recorded trips and general automation use per participant is provided in Table 1. For the Tesla drivers, data was collected successfully for 357 baseline and 431 experimental trips, while BMW drivers recorded 686 baseline and 1025 experimental trips.

Both the BMW and Tesla were equipped with full-range ACC and LK. The BMW ACC operated for speeds between 0–180 km/h while the Tesla ACC operated between 0–150 km/h. In the BMW, LK permits hands off steering wheel for up to 25 s. While enabled, the BMW system provides supporting steering inputs whenever system requirements are met (e.g. clear lane markings) and allows the driver to provide corrective steering without disabling the automation. We refer to standby when it is enabled while operating conditions are not met. Tesla LK (at the time) permitted 15 s of hands free driving and becomes unavailable for the remainder of a drive when this limit is exceeded 3 times. Tesla's LK has to be engaged by the driver and turns off when the driver provides corrective steering or braking. The BMW allows LK use with or without ACC enabled. The Tesla only allows LK while ACC is on.

2.1.1. Participants

For two participants (1 BMW, 1 Tesla), the demographic data was not available. The remaining 8 participants were all male, mean age 49 years (σ 5.2 years), licenced for 29.1 years (σ 6.2 years) and had driven 30,000 km to 40,000 km in the 12 months prior to the experiment. All participants indicated they felt "very interested" and "averagely" to "well" informed about the latest technological developments in the vehicle sector. Prior to the experiment, all but one participant normally used a vehicle equipped with cruise control, zero with adaptive cruise control or lane keeping assistance and three with lane departure warning. One participant (Tesla group) indicated to frequently use lane keeping assistance.

Table 1
Overview of the data collected.

	Baseline		Experimental		Experimental trips containing			
Participant	days	trips	days	trips	only manual	ACC&LK	Only ACC	Only LK
Tesla1	26	113	35	131	73 (56%)	57 (44%)	0 (0%)	
Tesla2	35	177	44	228	88 (39%)	137 (60%)	3 (1%)	
Tesla3	22	112	30	129	71 (55%)	53 (41%)	5 (4%)	
Total	83	401	109	487	232 (48%)	247 (51%)	8 (2%)	
BMW1	12	32	46	196	99 (51%)	86 (44%)	6 (3%)	5 (3%)
BMW2	32	111	48	154	31 (20%)	117 (76%)	0 (0%)	6 (4%)
BMW3	34	133	62	201	155 (77%)	41 (20%)	4 (2%)	1 (0%)
BMW4	20	62	35	109	40 (37%)	68 (62%)	0 (0%)	1 (1%)
BMW5	33	147	39	132	51 (39%)	78 (59%)	1 (1%)	2 (2%)
BMW6	36	116	7	22	10 (45%)	8 (36%)	0 (0%)	4 (18%)
BMW7	24	85	64	211	83 (39%)	126 (60%)	0 (0%)	2 (1%)
Total	191	686	301	1025	469 (46%)	524 (51%)	11 (1%)	21 (2%)

2.1.2. Instrumentation

Each vehicle was retrofitted with eight cameras observing the driver, instrument cluster, exterior in forward, left, right and rear directions, pedal bay and a top-down view towards the driver seat. The drivers were observed with 325x288 resolution at 10 Hz. The Tesla instrument panel was observed with 720x576 resolution at 25 Hz. Fig. 1 provides an overview of the available video feeds. A smart camera system (MobilEye) recorded lane position and surrounding road users. For map-matching, GPS and IMU data were collected at 1 Hz and 10 Hz respectively.

CAN-bus data was collected, from which various signals were reverse-engineered, including velocity, accelerations, steering wheel angle and torque, brake and accelerator pedal, turn indicator, lights, wind screen wipers, and (for the BMW) status information on the automation and warning systems (lane departure; collision). For the purpose of this study, only velocity and automation status were used. All signals except video were time-stamped. Video recordings were not synchronised but were watermarked with a human-readable timestamp.

2.2. Data preparation

A number of challenges emerged after data collection. Reverse engineering of CAN bus data to identify automation status was successful for the BMW but not for other vehicle types. GPS tracking, used for obtaining road type data, was not always available with sufficient accuracy. Additionally, some videos were corrupted and had to be omitted from the analysis. Table 2 shows data availability after filtering, synchronisation and re-sampling.

Two data enrichment efforts were performed for the analysis in this study. The first was to retrieve Tesla automation status by

Fig. 1. Overview of the eight camera perspectives recorded by the TNO instrumentation in the time-synchronized visualisation by SWOV for each vehicle. In reading order: right mirror view, forward view, left mirror view, driver face, instrument panel, rear view, driver seat, pedal bay. The driver's face is occluded for privacy reasons.

automatic detection of icons in the video of the instrument panel. Details on the implementation, training and validation are available in Appendix A and obtained 99.33% accuracy.

The second enrichment aimed to automatically annotate driver attention from video. Head pose was inferred instead of driver gaze because we were unable to measure this reliably. Several studies have suggested that head pose can be an acceptable gaze substitute when classifying attention into relevant regions of interest. Lee et al. (2018) have demonstrated that attention classification from head pose is feasible for on-road driving and obtained classification accuracies in the order of 83% and higher. Similarly, Braunagel (2017) used head pose as a fall back for eyes-on-road classification when gaze data was unavailable. Henni et al. (2018) showed that eye based features and head based features can achieve a similar classification performance for on-road drowsiness detection. Further implementation and validation details are available in Appendix B. While we were able to reproduce the per-class performance reported by Lee et al. (2018), overall classification accuracy was 69% and intersections over union metrics were below 50%, which is insufficient for attention analysis. This suggests that inferring attention from head pose is not feasible for driving scenarios, and demonstrates the importance of using appropriate performance metrics to judge classifier performance with unbalanced data. Lacking the means to classify driver attention per region of interest, this paper uses head pose variance as indicator for *possible* changes in attention behaviour.

3. Results

3.1. Automation usage

For the Tesla drivers, there were 16 baseline trips with very brief moments (0.2% of time on highways) of ACC or ACC&LK use. These are attributed to status classification faults. For the BMW drivers, there were 15 baseline trips (10 by one participant, 4 by another) where some form of automation was used (55% of time on highways). Trips where automation was used during baseline were excluded from analysis.

For automation use during the experimental condition, we first describe the distributions for both the Tesla and BMW drivers and then provide a statistical analysis. Automation status is observed with respect to road type, road speed limit, driving speed, time since the start of a trip and time of day.

During the experimental condition, all participants combined drove manually 50.4% of the time, 1.6% with ACC and 32.9% with ACC&LK turned on. BMW drivers had LK enabled without ACC in 16.5% of the time. Speed limiting was not used. Fig. 2 shows automation use by speed limit and road type. For both vehicles, most driving time was spent on the highway, and ACC&LK was used most here (Tesla: 63.0%, BMW: 56.6%). Manual driving was however preferred when negotiating highway links. Automation was used very little (<8%) on roads with speed limits below 70 km/h. In both vehicles, preference seems to be towards using ACC&LK over using either ACC or LK.

Fig. 3 shows how automation use changes with driving speed. Usage was generally low for driving speeds below 70 km/h. However during highway driving, automation use remained high at all speeds, with peak usage during slow stop-and-go traffic (0–30 km/h) and higher speeds (>80 km/h). Drivers of the BMW quite often used LK with ACC off, especially at reduced speeds (30–80 km/h) on the highway. This suggests that longitudinal automation was not preferred or not trusted in dense traffic conditions, while LK was. This did not happen for the Tesla drivers, since LK is not available while ACC is off. At higher speeds a sudden drop in automation use can be observed. This drop corresponds with the upper limit at which the vehicles make automation available.

Fig. 4 shows how automation use changes over the duration of a drive. After the first 10–20 min, automation use was relatively steady. The scatter at later times is an artefact resulting from the low number of long-duration trips. In the BMW data, a sudden drop in data availability occurs at 30 min. Since recordings are stored in 30 min segments, some data loss may have occurred during these transitions. Fig. 5 shows that automation use was uniform across the day for the Tesla drivers, while BMW users used more automated driving during commute hours (6 h-8 h and 16 h-18 h).

3.1.1. Statistics of automation use

To evaluate if automation use was influenced by time in trip, time of day and driving speed, we performed between-trips multilevel ANOVAs with participant as random intercept variable. Only highway driving is considered for these analyses. Table 3 provides the means and standard deviations for each category and variable and the statistical results. Effects are reported separately for the Tesla and BMW. Significance is also reported combining the two vehicles and thereby not considering standby mode and LK which are available only in the BMW. For significant factors, effect sizes are presented as differences in estimated marginal means in Appendix E. It should be noted that Table 3 and the histograms of Figs. 5, 4 and in particular 3 show different distributions. This is because the

Table 2
Data fraction available after pre-processing.

	Tesla	BMW
Automation status	100%	61.8%
Speed km/h	80.3%	61.8%
Allowed speed km/h	65.9%	60.4%
Road type	63.4%	52.3%
Head pose	72.4%	56.6%

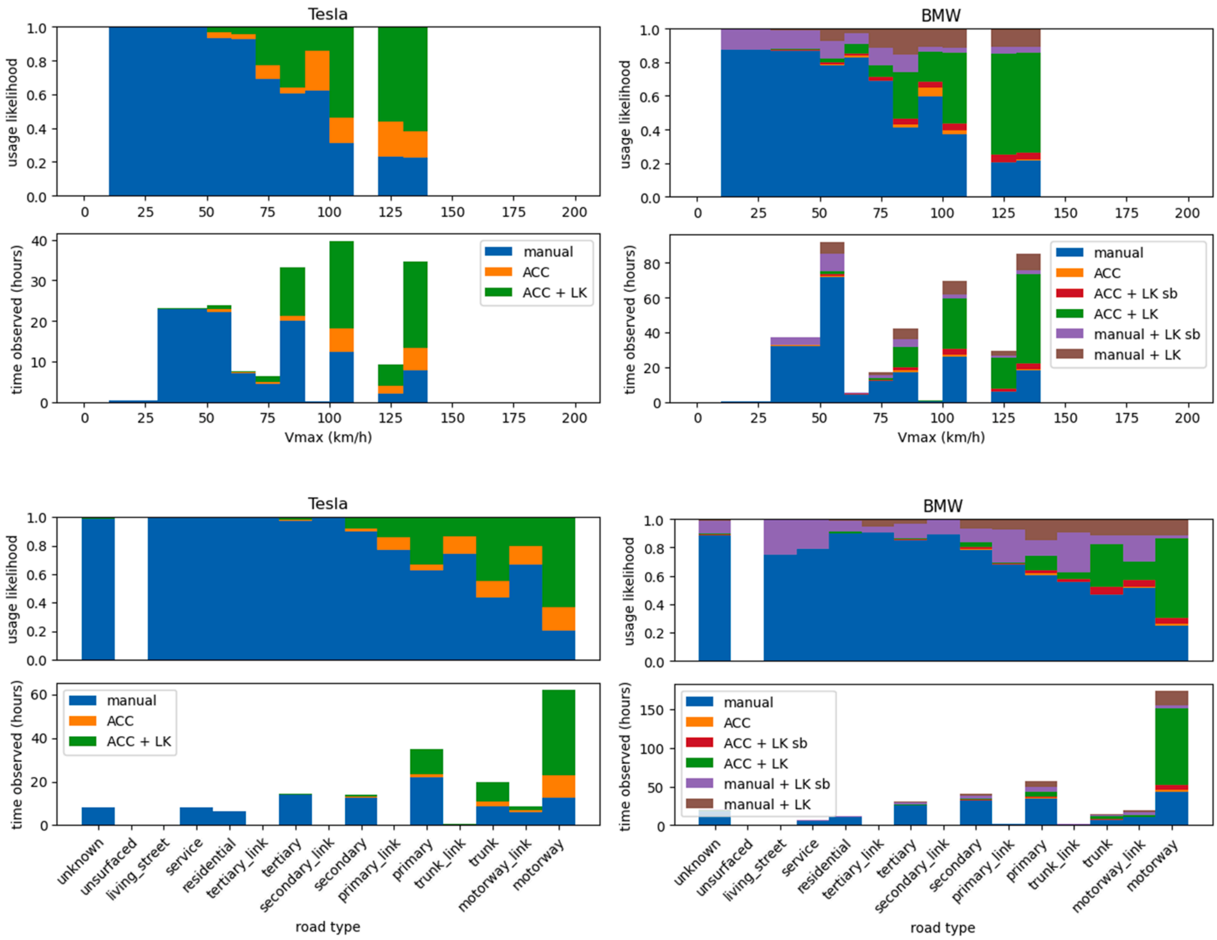

Fig. 2. Automation use for road speed limit (top) and road type (bottom). Road type was obtained by map-matching using OpenStreetMap (2004). LK_{sb} indicates lane keeping on standby. Type descriptions are provide.d in Appendix D.

histograms show total usage whereas Table 3 uses average usage per trip and does not account for trip duration.

Time in trip was split into three categories of 30 min each. The percentage of manual highway driving reduced from 40.0% to 27.5% after the first 30 min of driving and was replaced by a significant increase in ACC and an insignificant increase in ACC&LK use. The effect was consistent in both vehicle groups, but the ACC increase was only significant in the Tesla group. Table E.9 shows that Tesla drivers increased ACC use from 9.6% to 17.7% between the first and second 30 min of driving. Time in trip did not affect ACC&LK use. BMW drivers also increased LK use from 9.8% to 13.8% between the first and second 30 min of driving.

Time of day was split into five categories: night (23:00–4:59), morning (5:00–9:59), day (10:00–15:59), afternoon (16:00–18:59) and evening (19:00–22:59). For both vehicle types, night time driving was omitted from statistical analysis due to low sample size. For the Tesla group, effects of time of day on automation use were not significant. For the BMW group, automation use significantly changed with time of day for manual driving, ACC&LK use and LK use. There was no significant difference for ACC, ACC&LC_{sb} or LK_{sb}. Differences in estimated marginal means (Table E.8) suggest that ACC&LK use was significantly less during evening drives (38.5%) compared to all other moments. Compared to midday drives, LK was used 5.1% more during morning and 7.0% less during afternoon commute hours.

Highway driving speed was divided into categories adopted by Naujoks et al. (2016). Driving speed had a significant effect on all forms of automation use in both the Tesla and BMW users. Estimated marginal means (Table E.10) show that manual highway driving occurred the most at speeds between 10–60 km/h for both vehicle types. Conversely, ACC&LK (and to a smaller extent ACC&LK_{sb} for the BMW) occurred the least at these speeds. ACC usage increased significantly over speeds between 10 km/h and 100 km/h. In the BMW group, LK without ACC was used significantly more while driving 10–60 km/h compared to when driving 60–100 km/h, but not more compared to when driving > 100 km/h. Overall, the trend is towards more automation use (ACC or ACC&LK) at higher driving speeds. However, from a duration perspective, the overall ACC&LK usage in Fig. 3 suggests that ACC&LK was used at lower speeds as much as at higher speeds. This may relate to different behaviour during short and long periods of slow highway driving. Prolonged low speed driving was rare; only 11% of trips with slow highway driving contained more than 3 min. This suggests that ACC&LK was especially used during longer periods of slow highway driving, and less when such speeds were only reached momentarily, for instance

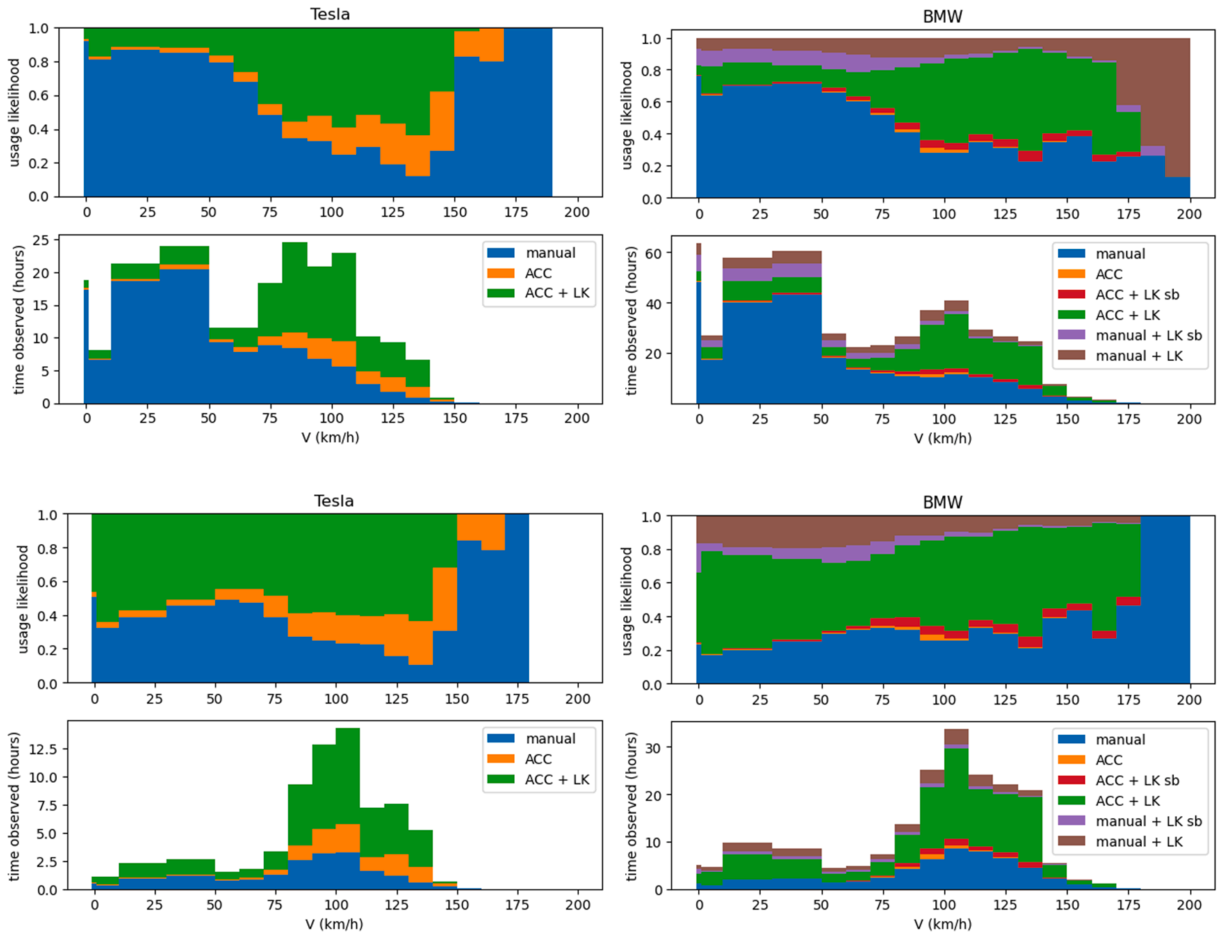

Fig. 3. Automation use as a function of vehicle speed for all road types (top) and highways (bottom).

when entering or leaving a highway at slow speeds, or when traffic slowed down momentarily.

3.2. Attention distribution

Since driver attention classification was unsuccessful, we evaluated if automation use changed the head pose distribution. This can indicate when and to which extent automation use changes monitoring behaviour. Head heading and pitch distributions (Figs. 6 and 7) were centred to the 50-percentile of each trip, and the standard deviation was compared across conditions. Statistical differences were explored during highway driving with a multilevel ANOVA using participant as a random intercept. For the BMW group, the standby variants ACC + LC_{sb} and LC_{sb} were excluded from this analysis. Table 4 shows that head heading and pitch were significantly affected by conditions in both vehicles.

Fig. 6 shows that more horizontal scanning occurred on road types where manual driving was preferred (e.g. roads with lower speed limits). On highways, head heading is similarly distributed across automation types. Fig. 7 indicates that Tesla users tended to face up more and face down less while using automation, whereas BMW users tended to have a wider distribution of pitch angles while using automation compared to manual driving. It should be noted that these behaviours are not informative on where the driver was looking, as demonstrated in Appendix B. These effects reduce when only considering highway driving.

For highway driving, Table 4 indicates that both heading and pitch deviation differed significantly between automation use for both vehicle types. The large sample size allows for statistically significant results even if effect sizes (Table E.11) are small. The effects followed the same trends for the BMW compared to Tesla drivers. Head heading deviation was smallest during ACC use (Tesla 12.0°, BMW 4.7°) and largest while driving manually in the experimental condition (Tesla 15.7°, BMW 10.2°). Interestingly, heading deviation in the baseline period (Tesla 13.5°, BMW 9.5°) was significantly smaller, but did not differ significantly from ACC&LK. For BMW users, heading deviation was also significantly smaller during LK (7.9°) compared to baseline.

For both groups, head pitch deviation did not differ significantly between baseline (Tesla 6.6°, BMW 5.1°) and experimental manual driving and was significantly smaller during ACC (Tesla 5.6°, BMW 3.2°) compared to all other conditions. Pitch deviation during ACC&LK did not differ from the manual conditions (baseline and experimental) for the Tesla group, but was highest (5.6°) in

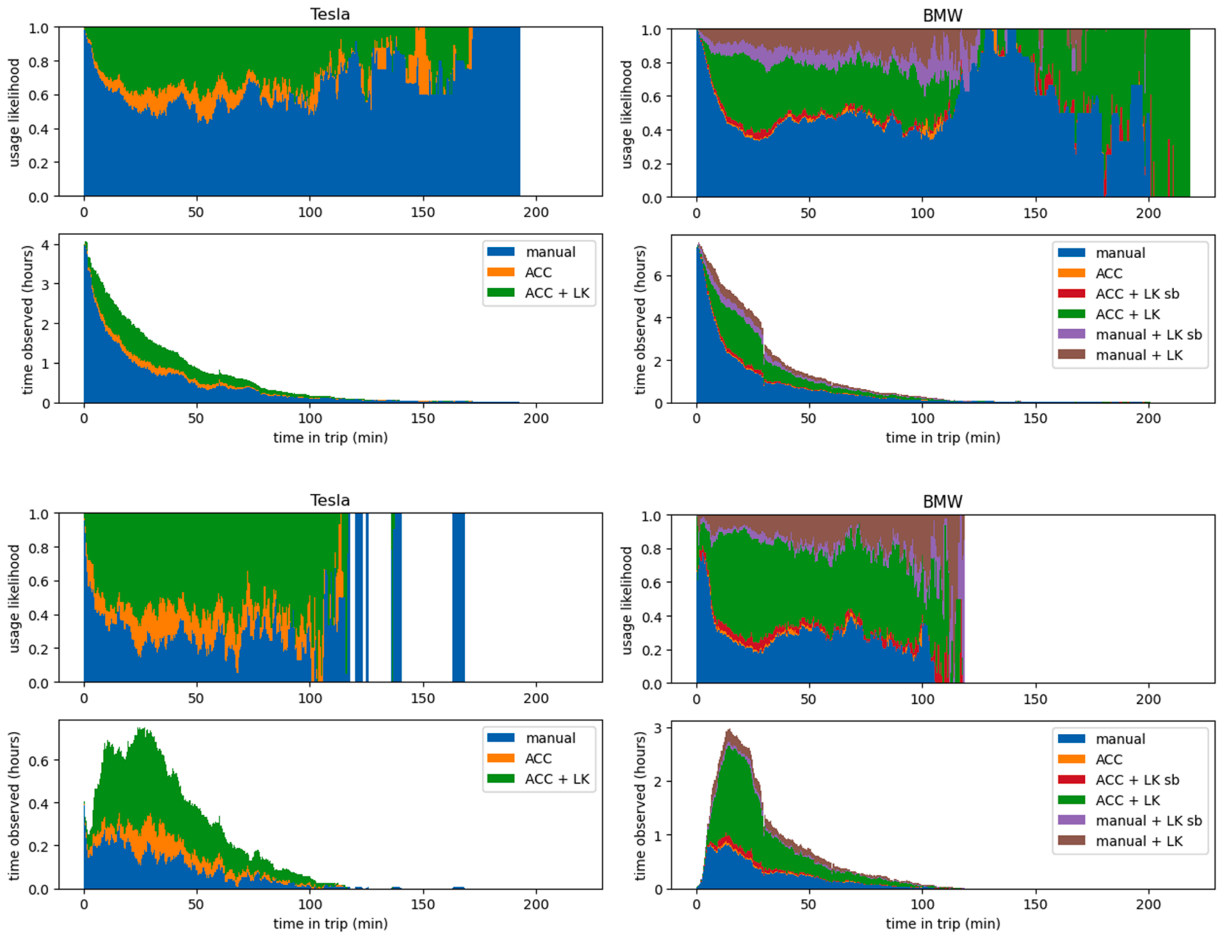

Fig. 4. Automation usage over time since the start of a trip for all road types (top) and highways (bottom).

the BMW group and significantly smaller (4.4°) during LK compared to the manual conditions, though the effect sizes are smaller than one degree (Table E.11).

3.3. Effects of experience

We evaluate how automation experience during the first 2 months of the experimental condition changed automation usage, and if experience affected attention as indicated by head pose deviation. To accommodate the limited sample size, experience is examined in 3 week periods. The baseline period is included for manual driving. Participant BMW6 is excluded from this analysis since only one week of data was recorded in the experimental phase. Statistics are in Table 5 and additional descriptives for automation usage over experience are given in Table E.12 which also includes the first day and first week of automation use.

For the individual vehicle models, there was no consistent change in automation usage over time; the effect is limited to weeks 6–9 where there was 9.5% less ACC&LK (p=.004) and 13.5% more manual driving (p<.001) in the BMW compared to Wk 1–3. When vehicle models are combined, automation usage did not change over the first six weeks, but ACC use decreased from 6.3% in weeks 3–6 to 1.0% in weeks 9–10, and manual driving increased from 24.7% in weeks 3–6 to 35.1% in weeks 7–9. ACC&LK use also tended to decrease over this period, but this effect was not significant.

Longitudinal changes in head heading and pitch deviation were examined as indicator for changes in attentive behaviour. Table 5 gives the main effects and Table E.13 provides pairwise comparisons for statistically significant effects.

For manual driving, head heading deviation was significantly smaller during baseline compared to the experimental phase, but did not change significantly over time within the experimental condition. During ACC, ACC&LK and LK use, head heading was not affected by experience.

Head pitch deviation changed significantly over time only for ACC&LK use, where it was 0.6° larger in weeks 7–9 compared to weeks 1–3. At later weeks, pitch deviation was similar to the first 3 weeks of automation use while using ACC&LK. Since the effect size is small and does not show a consistent trend, this was likely a consequence of uncontrolled differences between conditions, rather than a direct effect of experience.

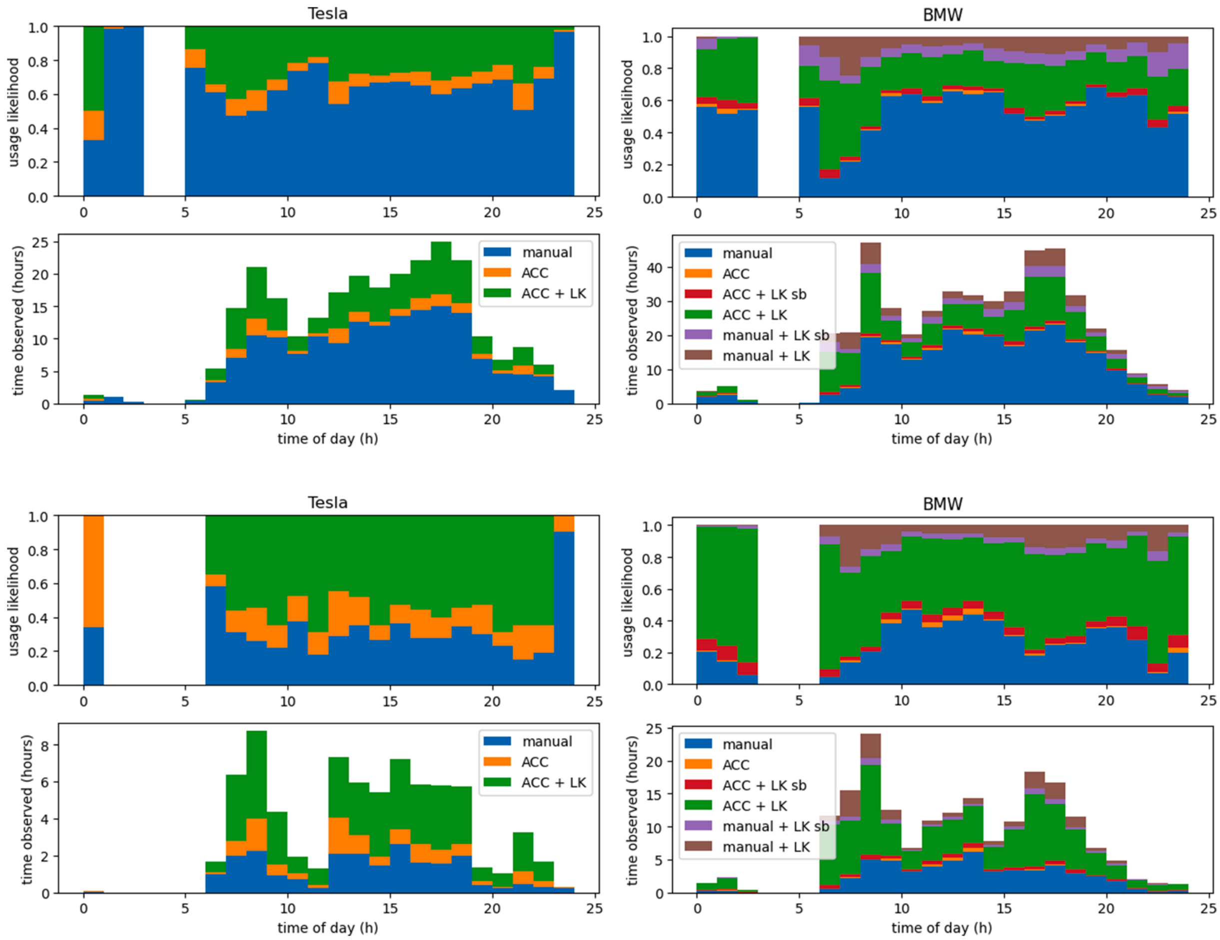

Fig. 5. Automation use over time of day (Amsterdam DST) for all road types (top) and on highway (bottom).

4. Discussion

This study analysed automation use across road types and speeds over the first two months of naturalistic use. Attention was evaluated using head pose deviation in heading and pitch.

4.1. Automation usage

For both vehicle models, ACC&LK was the dominant driving mode on highways, while roads with speed limits below 70 km/h were mainly driven manually. Level 2 automation (ACC&LK) was generally preferred over partial automation (ACC or LK) on highways. This high utility is in line with other usage studies (Russel et al., 2018; Nordhoff et al., 2016).

On highways, ACC&LK was used across all speeds including slow highway driving, but the least in moving congested traffic (30–80 km/h). Interestingly, Naujoks et al. (2016) found the highest secondary task uptake during automation use at these speeds. This is contradictory, since secondary task engagement requires a high willingness to use the automation. The difference may be caused by different trust levels between the vehicle models (Mercedes vs. Tesla, BMW), or the instruction to perform as many secondary tasks as possible in the controlled experiment.

Differences between total use time and per-trip averages suggest that manual driving was especially preferred when slow driving lasts shortly. This may include momentary slow-downs in traffic, but also transitions where the vehicle enters or leaves the highway. There may have been increased workload or reduced confidence in the automation's performance during such conditions. The BMW group used ACC less in congested traffic, whereas LK was used more. This suggests that unstable traffic flow impairs trust in longitudinal but not lateral automation performance. This distinction is not observed in the Tesla, where LK cannot be used without ACC. It is possible that some steering support utilisation is lost in the Tesla as a consequence.

Users were generally comfortable using automation during most highway conditions, and adapted their usage to the situation. Because use on urban roads was limited and incidental, participants were presumably aware of the system's general limitations and acted accordingly.

Table 3
Descriptives and ANOVAs for automation use on highway for various effects over experimental trips. Night driving (23–4) is excluded from the ANOVA because of small sample size.

			Time of day (hour)					Time in trip (min)			Speed (km/h)			
			23–4	5–9	10–15	16–18	19–22	0–30	30–60	60–90	0–10	10–60	60–100	>100
	nr. trips		3	45	97	60	34	212	103	43	95	155	160	155
	nr. participants		1	3	3	3	3	3	3	3	3	3	3	3
Tesla	Manual	μ	72.9%	47.3%	57.1%	55.3%	47.4%	52.2%	36.5%	38.4%	74.1%	79.0%	42.1%	29.2%
		σ	34.7%	37.8%	37.6%	40.8%	39.7%	38.9%	35.2%	35.0%	40.1%	32.4%	34.1%	33.4%
	ACC	μ	27.1%	10.8%	9.9%	8.2%	10.5%	9.6%	17.7%	13.5%	3.5%	3.9%	13.9%	16.3%
		σ	34.7%	13.7%	14.7%	14.6%	17.5%	15.4%	26.4%	22.5%	16.8%	12.9%	19.9%	20.6%
	ACC&LK	μ	0.0%	41.9%	33.0%	36.5%	42.1%	38.2%	45.8%	48.2%	22.3%	17.1%	44.0%	54.5%
		σ	0.0%	32.9%	31.8%	35.6%	36.0%	34.4%	34.3%	35.4%	37.6%	29.6%	30.9%	33.6%
	nr. trips		22	144	197	142	69	526	191	68	334	510	538	523
	nr. participants		4	7	7	7	7	7	4	4	7	7	7	7
BMW	Manual	μ	25.0%	22.4%	40.0%	29.4%	51.0%	34.3%	29.5%	34.6%	39.4%	48.2%	38.4%	31.0%
		σ	25.5%	33.6%	40.9%	39.1%	42.1%	39.8%	38.8%	42.2%	46.9%	46.0%	41.3%	39.9%
	ACC	μ	2.3%	1.2%	1.5%	1.1%	0.2%	1.1%	1.7%	1.0%	0.3%	0.4%	1.5%	0.9%
		σ	0.9%	6.6%	7.6%	5.8%	0.4%	6.5%	10.2%	4.6%	2.5%	3.1%	7.7%	6.1%
	ACC&LK^{sb}	μ	7.8%	5.1%	5.6%	4.2%	3.8%	5.0%	5.3%	3.2%	0.8%	2.1%	5.7%	5.8%
		σ	5.2%	6.0%	6.6%	5.8%	4.5%	6.5%	10.1%	5.4%	8.1%	10.3%	9.7%	8.3%
	ACC&LK	μ	60.5%	56.0%	42.3%	47.9%	34.8%	47.2%	44.7%	40.8%	21.3%	15.7%	38.8%	51.8%
		σ	26.2%	29.7%	32.8%	35.7%	33.7%	34.5%	32.0%	31.1%	36.4%	29.9%	33.1%	36.2%
	LK^{sb}	μ	1.9%	4.7%	4.1%	4.8%	3.9%	4.0%	6.6%	6.9%	22.4%	22.7%	6.7%	2.5%
		σ	3.8%	5.2%	8.6%	9.5%	8.5%	8.2%	16.5%	13.2%	39.3%	35.3%	12.5%	6.7%
	LK	μ	2.5%	10.7%	6.5%	12.5%	6.3%	8.3%	12.1%	14.0%	15.8%	11.0%	9.0%	8.0%
		σ	6.6%	15.8%	11.6%	21.0%	12.7%	15.8%	19.5%	17.6%	32.1%	21.5%	16.3%	17.0%

		Time of day		Time in trip		Speed	
		F	p	F	p	F	p
Tesla	Manual	F(3, 231.2)=0.603	.613	F(2, 354.0)=5.257	.006	F(3,559.2)=72.738	<.001
	ACC	F(3, 231.4)=0.312	.817	F(2, 355)=5.689	.004	F(3,561)=18.937	<.001
	ACC&LK	F(3, 231.3)=0.639	.591	F(2, 354.0)=1.353	.260	F(3, 559.2)=44.587	<.001
BMW	Manual	F(3,542.8)=6.096	<.001	F(2,778.3)=9.015	<.001	F(3, 1895.1)=24.039	<.001
	ACC	F(3,544.9)=0.882	.450	F(2, 752.3)=0.406	.666	F(3, 1897.2)=4.376	.004
	ACC&LK$_{sb}$	F(3,543.4)=1.643	.178	F(2, 780.3)=3.514	.030	F(3, 1895.5)=34.641	<.001
	ACC&LK	F(3,542.5)=3.716	.011	F(2, 778.2)=0.268	.765	F(3,1895.1)=150.453	<.001
	LK$_{sb}$	F(3,544.4)=0.251	.861	F(2, 780.4)=11.459	<.001	F(3, 1895.3)=29.808	<.001
	LK	F(3,542.7)=7.272	<.001	F(2, 779.4)=4.451	.012	F(3, 1895.2)=10.861	<.001
Combined	Manual	F(3,776.5)=3.597	0.013	F(2,1134.2)=14.086	<.001	F(3,2457.2)=65.406	<.001
	ACC	F(3,778.7)=0.410	0.746	F(2,1137.6)=6.078	0.002	F(3,2457.1)=20.668	<.001
	ACC&LK	F(3,776.4)=2.155	0.092	F(2,1135.0)=1.208	0.299	F(3,2457.1)=194.918	<.001

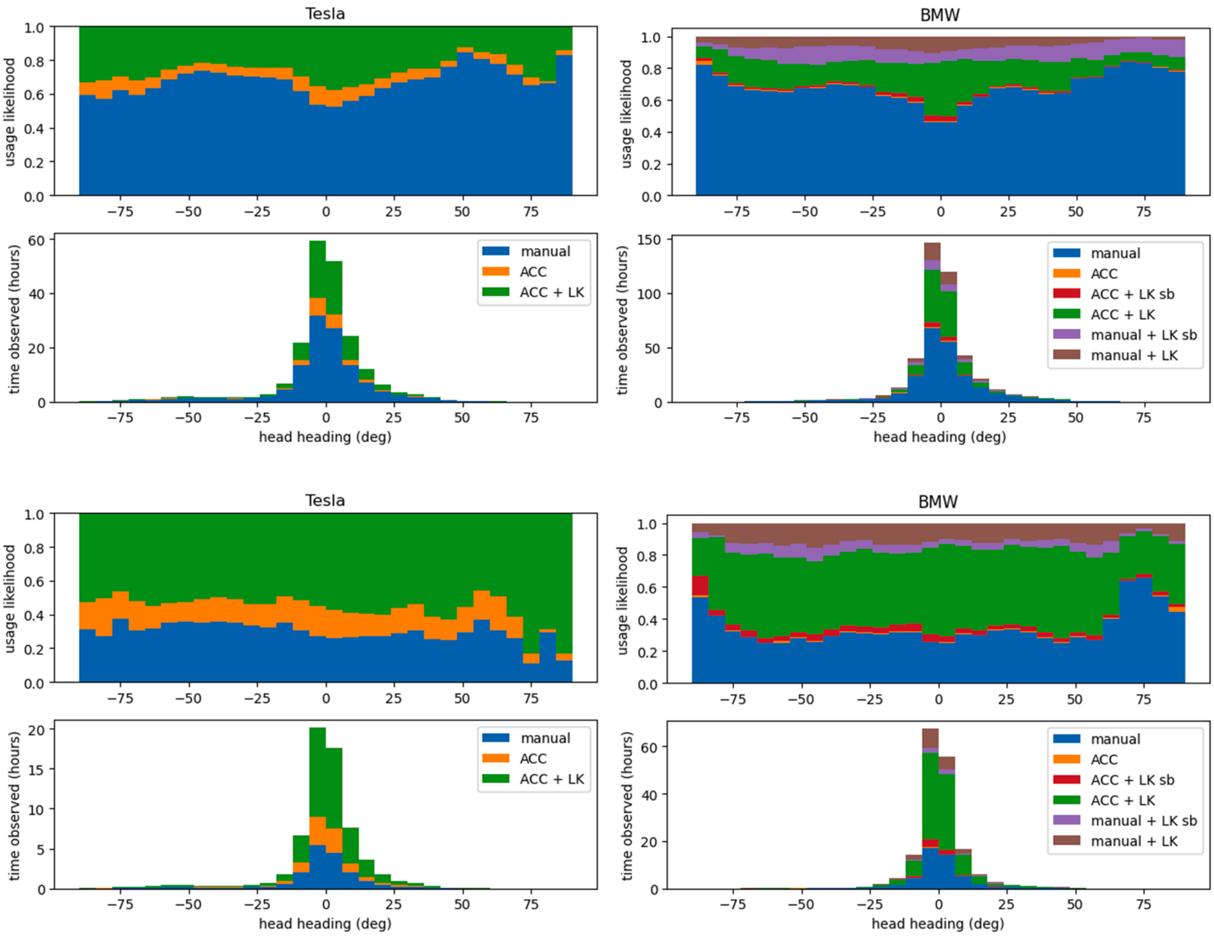

Fig. 6. Distribution of head heading on all road types (top) and on highways (bottom). Positive heading indicates looking to the right.

Time-in-trip effects indicate reduced manual driving on highways after 30 min for both driver groups. The effect does not persist over longer trips, but statistical poser also reduces as fewer long trips are available. The manual driving was consistently replaced by an increase in ACC, LK and ACC&LK usage, tough these effects were only statistically significant for ACC use in the Tesla group and LK use in the BMW group. This suggests that automation use is used more on longer trips, which may be related to an increase in fatigue during such drives.

The effects of time of day were only significant for BMW drivers and did not show a consistentrelation between automation use and commute hours (where road familiarity tends to be higher (Young et al., 2017)) or circadian rhythm (where sleepiness susceptibility increases at night and late afternoon (Zhang, Yan, Wu, & Qiu, 2014)). Time of day therefore does not suggest a clear tendency to use or avoid automation use at particular times.

No longitudinal experience effects on automation use were observed over the first 6 weeks of automation use. The amount of manual driving increased and ACC use decreased after this, but no effects were found for the dominantly used ACC&LK. It is possible that most experience effects occured over a shorter period, possibly within a small number of trips. For instance, Beggiato et al. (2015) demonstrated that a driver's mental model of ACC converges within 3.5 h of use. On the other hand, Larsson (2012) demonstrated that ACC users keep refining their awareness of system limitations over the first 10 months of use. It is possible that such adaptations are not expressed through overall metrics such as system usage.

4.2. Attention distribution

While we were unable to classify driver attention among attentive and driving unrelated areas, the analysis of head pose deviation identified small but significant trends in visual monitoring.

On the highway, head heading and pitch deviation were smaller during ACC use compared to other driving modes, including baseline manual driving. Deviations during ACC&LK did not differ from baseline. These trends contradict Louw and Merat (2017) and Morando et al. (2019) who found automation to increase horizontal gaze dispersion by 1.4° and reduce median percent road centre by 3%. Possible explanations for this difference include the used metrics (gaze vs. head pose) and not controlling for periods of following a

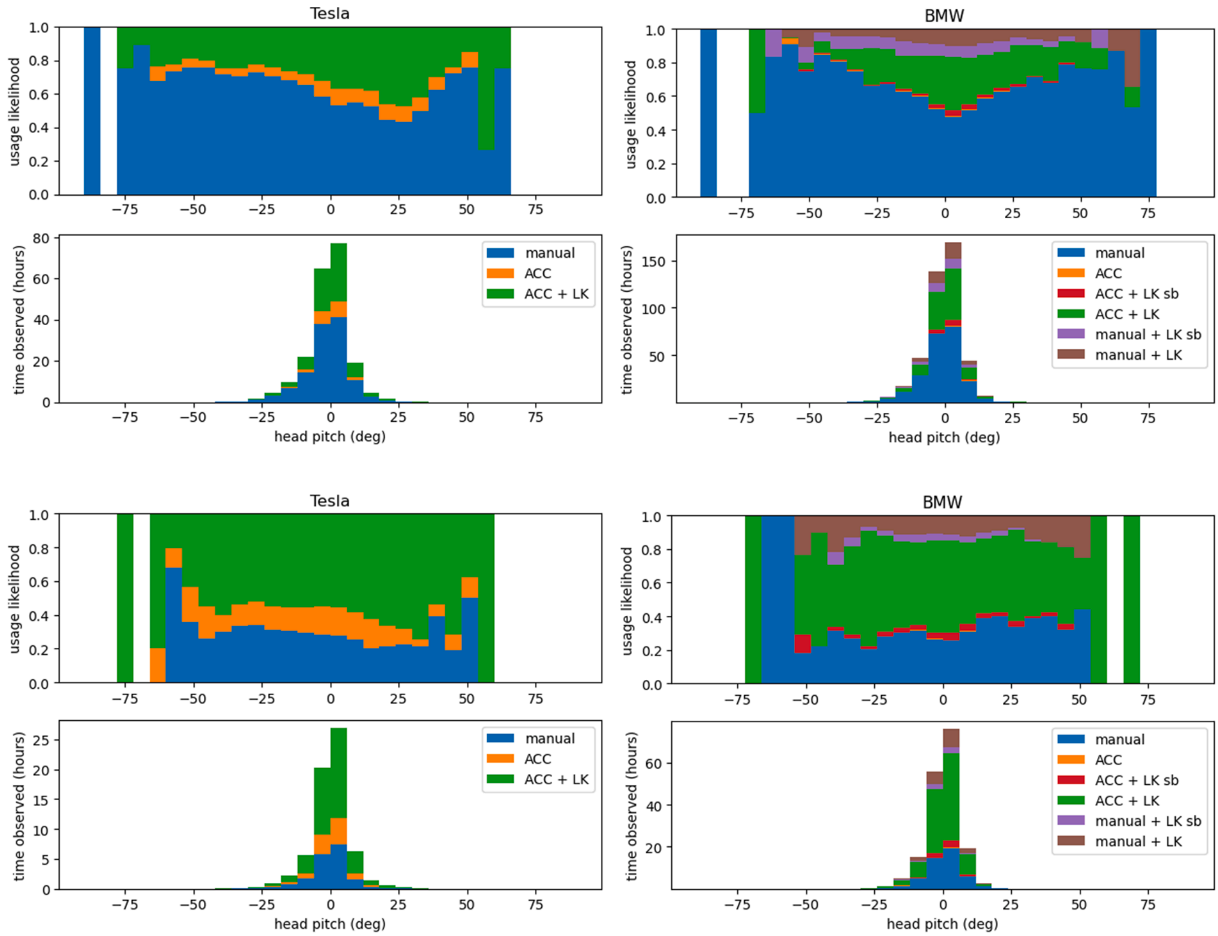

Fig. 7. Distribution of head pitch on all road types (top) and on highways (bottom). Positive pitch is upward.

Table 4
ANOVAs for effects of automation use on head heading and pitch deviation.

	Heading		Pitch	
Tesla	F(3,583.0)=12.243	<.001	F(3, 581.2)=8.412	<.001
BMW	F(4, 1595.4)=79.286	<.001	F(4, 1593.7)=70.542	<.001
combined	F(4, 2178.8)=63.813	<.001	F(4, 2178.7)=61.914	<.001

Table 5
Main effects of experience (wk 1–3, wk 4–6, wk 7–9, wk 10–12) on usage and head heading and pitch deviation for highway driving in the experimental condition. ANOVAs are corrected for individual differences. Baseline condition is only included for Head variance during manual driving.

		Usage		Heading		Pitch	
		F	p	F	p	F	p
Tesla	Manual	F(3, 145.2)=0.241	.868	F(4, 309.0) = 3.659	0.007	F(4, 316.1) = 1.329	0.259
	ACC	F(3, 156.0)=1.196	.313	F(3, 129.0) = 2.032	0.113	F(3, 121.2) = 2.206	0.091
	ACC&LK	F(3, 114.3)=1.001	.395	F(3,121.6) = 2.528	0.061	F(3, 128.0) = 7.611	<.001
BMW	Manual	F(3, 513.7)=5.104	.002	F(4, 628.6) = 15.234	<.001	F(4, 627.9) = 2.687	.030
	ACC	F(3, 516.9)=1.968	.118	F(3,151.7)=2.112	.101	F(3, 150.99)=4.812	.003
	ACC&LK	F(3, 513.6)=2.851	.037	F(3,379.6)=0.504	.680	F(3, 379.4)=0.481	.696
	LK	F(3, 515.4)=0.623	.601	F(3, 342.4)=0.181	.909	F(3, 341.5)=0.083	.969
Combined	Manual	F(3,674.5)=4.717	0.003	F(4,948.5)=8.205	<.001	F(4,948.4)=1.279	0.277
	ACC	F(3,675.1)=2.970	0.031	F(3,283.3)=0.022	0.996	F(3,282.5)=0.801	0.494
	ACC&LK	F(3,674.2)=1.519	0.208	F(3,511.0)=1.723	0.161	F(3,511.4)=3.500	0.015

lead vehicle (which for Morando et al. (2019) increased percent road centre by 4%). Whether the lower head pose deviation during ACC should be interpreted as an increase or decrease in monitoring intensity (or as a spurious effect) remains to be investigated. If drivers were mostly monitoring attentively during automation, lower deviation could indicate an increase in attention to road centre or cognitive narrowing due to an increased mental demand. However, it can also be caused by cognitive load from driving-unrelated thoughts (Victor et al., 2005; Wang et al., 2014), a reduced perceived need for visual scanning, or an increase in mind wandering (He, Becic, Lee, & McCarley, 2011). Even when gaze had been obtained in addition to head pose, identification of the correct cause may be challenging since even for gaze dispersion it is not certain if a wider deviation represents more distraction or a better monitoring strategy (Grüner & Ansorge, 2017). Classification of attention to driving related and unrelated areas may provide more insight but requires gaze observation.

Heading deviation was larger during manual driving in the experimental phase compared to baseline. This could be caused by the voluntary use of automation in this study: drivers may have prefered to drive manually in situations which required more head deviation, such as when changing lanes (Goncalves, Louw, Quaresma, Madigan, & Merat, 2020).

Important to note is that the effect of ACC&LK on heading deviation depends on whether it is compared against baseline-manual (no difference) or experimental-manual (ACC&LK reduces heading deviation). This may raise caution for studies which compare attention between manual and automated driving without providing a manual baseline. Automation effects on head pitch deviation were very small and unlikely to carry practical significance.

Besides the difference in head heading deviation between baseline and experimental manual driving, no longitudinal changes in head pose deviation were found which could indicate effects of experience on monitoring. Possibly such effects were not observable, either through the metrics used or confounding variance.

4.3. Limitations

This study includes 10 participants and two vehicle types. This sample size is too small to generalise findings to a larger population. Therefore, only the larger and consistent effects should be considered indicative. Another limitation is the use of head pose as indicator of attention. We demonstrate that driver head pose is not predictive of attended region of interest. While we argue that a change in head deviation can indicate a different monitoring strategy, we provide no suggestions on how such change should be interpreted with regards to better or worse monitoring, or its safety implications.

4.4. Suggestions for future research

Since few effects were observed for aggregate factors such as experience and time of day, future work could more closely examine motivations for automation use and disuse. Such information could be acquired through interviews with drivers or a close examination of the traffic situation when control transitions are taking place.

Our second recommendation is related to head pose. Since head pose tracking without gaze direction was insufficient for attention classification, we recommend gaze monitoring for future work on naturalistic attention monitoring.

Finally, for future research it would be interesting to study if different system interaction designs impact the effectiveness and usability of the automation, and how this differs across various user groups. Such insights could help formulate design choices that benefit safety and ease of use. Intuitiveness and ease of use of the systems are crucial for the adoption and safety of automation. Systematic evaluation can aid design guidelines for safe user interaction. Such guidelines would support industrial parties in designing safe and intuitive interfaces and support policy makers to evaluate new systems and set clear requirements for admission.

5. Conclusions

5.1. When and in which conditions do drivers use ACC and LK support?

ACC and LK were mostly used on road types for which the systems are intended. On highways ACC&LK was used 63% of the time by the Tesla group and 57% of time by the BMW group. It was used least in moving congested traffic (30–80 km/h) where ACC&LK was mainly replaced by LK (BMW) or manual driving (Tesla), which could mean that especially ACC is not preferred in unstable traffic. On urban roads and roads with speed limits below 70 km/h, automation was used less than 8% of the time, which suggests that users were aware of the system's general limitations in those conditions. Automation use was not clearly affected by time of day. Time-in-trip suggests that manual driving occurs less after 30 min of driving, which suggests automation use is favoured in longer drives. These observations may help to evaluate if there is good overlap between the application domain and operational design domain.

5.2. Is driver attention different during manual driving and driving with supervised automation?

We found limited changes in monitoring behaviour with supervised automation. Head movement activity was smaller on highways compared to other road types. On highways, head pose activity during ACC&LK did not differ from baseline manual driving, but was smaller during ACC use. Head heading deviation was larger during manual driving in the experimental phase compared to manual driving in the baseline phase. This motivates further research into the nature and cause of these changes. This also means that studies can risk making incorrect inferences about automation effects on attention when only sampling manual and automation conditions during voluntary use without a baseline condition with instructed manual driving.

5.3. Do these behaviours change with automation experience?

There was no consistent change in automation usage over time. Similarly, changes in head motion activity could not be attributed to a simple experience effect, and are more likely a consequence of uncontrolled differences between conditions.

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 material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.trf.2022.08.013.

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Further reading

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