Benefits of Extended Multisensory Space during Automated Driving

Master Thesis

Human Factors and Engineering Psychology

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Abstract

With rapid advances in automated driving technology, safe methods for transition between automated and manual driving are still being investigated. Research has shown that using hand-held tools can lead to an extension of peripersonal space – the space immediately surrounding the body. Furthermore, interoceptive physiological inputs, coupled with visual feedback can modulate bodily self-consciousness and thus lead to changes in participants' peripersonal space. An extension of drivers' peripersonal space around the car could thus lead to improved takeover performance when confronted with a takeover request in a simulated Level 3 automated vehicle. Therefore, we hypothesised that synchronisation of ambient lighting inside a car with participants breathing would lead to faster reaction times and a smaller lateral displacement when a takeover request is issued. We did not find any strong enough evidence to support our hypotheses. However, we think that a multidisciplinary approach to Human-Vehicle Interaction is needed to ensure safe takeover methods when drivers are confronted with a takeover request in a Level 3 automated vehicle.

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Introduction

With rapid development of automated driving (AD) technology, all major car manufacturers implement self-driving features in their vehicle line-ups. While the benefits of self-driving cars are expected to be increased safety, fewer traffic problems, less accidents and an increase of leisure and work time (Nees, 2016; Pfleging et al., 2016), self-driving cars also give rise to a number of problems. These challenges concern ethical issues (Geisslinger et al., 2021), technical challenges (Thakurdesai & Aghav, 2021), legal challenges (Vellinga, 2017), but also human factors challenges (Gillmore & Tenhundfeld, 2020). Among the biggest challenges in human factors are safe transitions between automated and manual driving. In situations where the AD system does not have the required capabilities to function safely and reliably, drivers need to regain manual control of the vehicle. Although several design solutions have been tested (e.g. Borojeni et al., 2016; Wintersberger et al., 2018), there is still no consensus on how this transition can be safely realised. In this study, we propose a novel approach to realise safe transitions from automated to manual driving.

1.1 SAE Levels of Automation

As functions and capabilities of AD systems vary immensely between vehicles and equipment, classifications are needed to compare those functions. One of the most often used classification are the six levels of driving automation (SAE J3016, see Figure 1), by the Society of Automotive Engineers (SAE, 2021). On the base level (Level 0) the vehicle is not equipped with any driving automation features, therefore, the driver is always in control of dynamic driving tasks. Nevertheless, this does not imply that no safety systems can be equipped in the car. Active safety systems such as anti-lock braking system, electronic stability control or automatic emergency braking are not regarded as driving automation, as these systems only provide momentary assistance at driving dynamic limits or/and hazardous situations (SAE, 2021).

Level 1 automation, termed driving assistance, includes driving assistance systems that control either longitudinal or lateral driving parameters. For example, Adaptive Cruise Control (ACC), a radar-based distance keeping cruise control, is regarded as an automation level 1 feature (SAE, 2021). Level 2, "partial driving automation", entails driving systems that control both longitudinal and lateral control of the vehicle. However, these systems require the driver to monitor those functions and intermittently touch the steering wheel to avoid misuse of the system (SAE, 2021). Level 0 to Level 2 are therefore termed driver support features, as the human driver is still in control of the vehicle (SAE, 2021). Nowadays, a variety of premium and mainstream car manufacturers include Level 2 AD technology in models of their line-up (Meier, 2021)

Level 3 automation, "conditional automation", includes systems that can perform driving tasks when certain requirements are met (e.g., driving on highways). However, if these systems encounter a situation that cannot be handled by the vehicle itself, a takeover request is issued, leading to human intervention and control. Level 4 ("high automation") and Level 5 ("full automation") systems do not require any human intervention at any time. While Level 4 systems may operate in limited areas (e.g., local driverless public transport), Level 5 systems operate unconditionally in all situations.

Figure 1

SAE J3016 Levels of Driving Automation (SAE, 2021)

1.2 Takeover Requests and Takeover Performance

In most of today's cars, drivers are always in control of the vehicle and monitor the driving environment. Therefore, they are cognitively engaged in the driving task and thus are "in-the-loop" (Merat et al., 2019). However, Level 3 and higher equipped cars give the opportunity for the driver to engage in non-driving related tasks, like smartphone use. Once a driver neglects the task of monitoring the driving environment – both in manual and automated mode - the driver is out-of-the-loop (Merat et al., 2019). Getting the driver back into the loop is considered one of the biggest issues in automated driving technology (Casner et al., 2016).

As Level 3 automated driving systems have operational limits, human drivers must regain control once a feature limit is reached. To alert the driver of an upcoming system limit, takeover requests (TOR) are issued. To alert the driver, several types of TOR modalities are used. Common types are auditory signals (e.g., notification tones), visual cues (e.g. flashing icons) and tactile signals (e.g., vibrating seats). Morales-Alvarez et al. (2020) conducted a literature study on different takeover (TO) modalities and showed advantages and disadvantages of the respective types. Visual cues in form of images have the advantage of transmitting a large amount of information, however, such information can still be missed by distracted drivers. Ambient visual cues, such as a flashing light bar integrated in the dashboard can be easily detected by distracted drivers. However, they might not understand what message a specific lighting pattern conveys (Morales-Alvarez et al., 2020). Auditory cues have the advantage that drivers do not need to take their eyes off the road, but the message might not be clear to understand, and urgent information requires longer time to transmit. Tactile information also enhances drivers' auditory and visual perception. However, only a limited amount of information can be communicated, as multiple messages via, for example a vibrating seat, are not intuitive to understand (Morales-Alvarez et al., 2020).

Converging evidence from literature investigating TO modalities suggests that a combination of TOR styles works best in informing the driver of an upcoming system limit or a critical – high urgency – situation (Bazilinskyy et al., 2018; Petermeijer et al., 2017; Yoon & Ji, 2019; Yun & Yang, 2020). In low-urgency scenarios (e.g., planned exit of highway), Bazilinskyy et al. (2018) found that auditory signals were preferred over visual and tactile signals.

However, once a TOR is issued, drivers' response to the prompt is influenced by several aspects, and performance varies across drivers and systems. First, situational awareness (SA) is one of the main factors which need to be considered. Endsley (1995) defines SA as the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future. Applied to the TOR, the takeover time needed depends on the duration of gathering and comprehending environmental inputs and the transfer of this meaning onto the current situation (Gold et al., 2013).

Furthermore, cognitive workload and distraction during AD also play crucial roles in takeover performance. Du et al. (2020) found that drivers with a high cognitive workload had a lower takeover readiness and a worse takeover performance, compared to participants with low cognitive load. In their study, participants cognitive load was manipulated by different difficulty levels of the N-back-task (Du et al., 2020). However, in line with the Yerkes-Dodson law (optimal level of arousal), Ma et al. (2020) found that drivers with a moderate level of cognitive workload had significantly shorter takeover times and better takeover performance, compared to drivers with too high or too low cognitive workload. Zhang et al. (2019) conducted a meta-analysis of 129 studies and found that takeover times (TOT) were substantially higher when drivers used hand-held devices. Takeover performance was also influenced by the time available until the system limit is reached (Zhang et al., 2019).

Gold et al. (2013) found that the longer the provided TO time was, the longer was the decision period of the drivers to regain SA and plan their action. With lower provided TO-time, the quality of the TO decreases, as not enough time is available to come to a proper decision. Furthermore, drivers who did not have enough time during the TOR, used hard braking to slow down the vehicle and thus increase the time available to make a decision (Gold et al., 2013). Lastly, previous familiarisation with the AD-system and the display/function of the TOR were proven to have a positive influence on takeover performance (Forster et al., 2019; Hergeth et al., 2017; Payre et al., 2016).

1.3 Space Representation and Peripersonal Space

Even though we perceive space as unitary, neuroscientific evidence shows that the brain contains modular representations of space (Cléry et al., 2015; Harrison, 2015; Rizzolatti et al., 1997; see Figure 2). Space is represented in three different proximities around the body. First, personal space – the space on the surface of our body. Second, extrapersonal space – the space that is unreachable by arm movements (Costantini et al., 2010). In between personal and extrapersonal space lies the peripersonal space (PPS) – the space immediately surrounding our body and in which objects can be manipulated (Costantini et al., 2010; di Pellegrino & Làdavas, 2015; Masson et al., 2021; Rizzolatti et al., 1997; Serino, 2019). Each of these spaces involve separate cortical areas in the brain, which process information about different multi-sensory inputs. This information is then pooled in, primarily, the temporal and parietal lobes (Cléry et al., 2015).

Figure 2

Space representation around the human body. Light grey area displays extrapersonal space. Dark grey area displays peripersonal space and light blue area displays personal space.

One important characteristic of PPS is its plasticity; it can be modified by experience. Guterstam et al. (2018) found that active use of tools leads to an extension of the peripersonal space around the used tool. Osiurak et al. (2012) found that even when passively holding a long grasping tool, participants underestimated the distance to an object they were instructed to grasp. These and other findings (see Holmes et al., 2004; Iriki et al., 1996), suggest that the tool used by the human modifies the body schema due to peripersonal plasticity. Further studies revealed that planning to grab an object strengthens the multisensory interaction of visual information from the object and the (somato)-sensory information elicited by visual- and tactile receptive fields in the hand (Patané et al., 2019). Furthermore Maravita and Iriki (2004) stated, that by using a tool, peripersonal space is extended and it would thus produce similar behavioural effects as reaching for close-to-hand stimuli. Importantly, not only physical objects can be embodied, but also virtual objects. Mine and Yokosawa (2021) showed that a virtual hand was also integrated into participants' peripersonal space.

Even though evidence on peripersonal space extension through tool use is well established, hardly anything is known about the way these perceptions affect the use of a vehicle (Moeller et al., 2016). Galli et al. (2015) found that using a wheelchair extends and modulates peripersonal space. Likewise, reports from racing drivers potentially suggest that their felt connection to the car and their knowledge of exact placement of the vehicle within space, involves an extension of PPS.

1.4 Visuo-Respiratory Synchronisation

Research has shown that exteroceptive (signals from outside the body, e.g. tactile) and interoceptive (signals from inside the body, e.g. respiration) inputs that are synchronised with sensory feedback (visual, auditory, or tactile) can also enhance participants' self-identification with objects (Aspell et al., 2013; Tsakiris & Haggard, 2005). Self-identification refers to experiencing one's self as located within an owned body (Noel et al., 2015). This effect can be explained as changes in perception of PPS (D'Angelo et al., 2018). One potent example of this concept is the rubber hand illusion (RHI), in which a rubber hand is synchronously stroked with the hand of the participant. Due to this synchronous stroking, participants perceive the rubber hand as their own (Botvinick & Cohen, 1998). However, when the two hands are stroked asynchronously, the illusion is not present. Research by Adler et al. (2014) and Aspell et al. (2013) found that this illusion is also present when interoceptive physiological inputs are coupled with visual feedback. In Aspell et al. (2013) study, a visual pattern was synchronised with participants' cardiac activity which then was projected on a virtual avatar. This led to an increase in self-identification with the virtual avatar (Aspell et al., 2013; Heydrich et al., 2018). On the contrary, synchronisation of participants' respiration with a visual pattern (visuo-respiratory) did not lead to a higher sense of body ownership (Adler et al., 2014). Nevertheless, visuo-respiratory synchronisation induced a change in breathing perception. Participants indicated that they felt as the act of breathing was related to the virtual avatar (Adler et al., 2014). Also, breathing does not only have an interoceptive factor (e.g., sensation of rib cage movement), but also an exteroceptive part. Breathing establishes a link between one's body and the surrounding environment by, for example, contributing to the perception of temperature changes and odours (Adler et al., 2014). Therefore, respiration is at the crossroad between exteroception and interception (Adler et al., 2014) Furthermore, other studies have shown that participants interact faster with a virtual object or avatar if it is illuminated in synchrony with participants' heartbeat (Heydrich et al., 2021).

1.5 The present study

As there is still no consensus on how to ensure a safe transition from automated to manual driving, this study investigates the benefits of an extended peripersonal space to achieve better takeover performance. Grounded on the assumption that controlling vehicles affects PPS in similar ways to using hand-held tools, respiration rate was coupled with the ambient lighting in a simulator-based automated vehicle with level 3 technology. We decided to use breathing, as it is an unobtrusive measurement, compared to measuring cardiac activity. Furthermore, we assumed that participants would notice a sudden disruption of their breathing pattern more clearly than a sudden change in their heart rate pattern.

In our experiment, participants were divided into three groups. In the Sync group, ambient lightning was synchronised with participants’ respiration; in the Async group there was no synchronisation, and the visual feedback pulsated randomly. In the Repetitive condition, visual feedback pulsated constantly with the same rate, unrelated to the breathing pattern. Async and Repetitive conditions were control conditions.

We expected that (1) PPS of participants in the Sync condition would expand around the body of the car (see Figure 3) and that, as a result, the sudden disruption of the Sync pattern would lead to faster reaction times. Furthermore, we expected that (2) lateral displacement in the synchronous condition would be lower. Additionally, to gain further information about the effect of the manipulation, we hypothesised that (3) participants in the Sync condition would be less physiologically aroused and that (4) trust would be higher in the Sync group compared to controls, as participants might establish an unconscious connection to the vehicle and thus, would be more at ease with the automation. Lastly, we assumed that (5) self-identification with the vehicle would be higher in the Sync condition, due to visuo-respiratory synchronisation.

Figure 3

Hypothesised extension of PPS. Due to visuo-respiratory synchronisation, the PPS extends from around the driver (left) to around the car (right).

Method

2.1 Participants

The experiment was completed by 36 participants who were recruited via SONA systems, a platform for acquiring participants at the University of Twente. For taking part, participants received 1.5 credits. Twelve participants were excluded from the analysis due to not being naïve, having no driving experience or misunderstanding the takeover procedure. The final sample consisted of 27 participants who were male (n=11) and female (n=16), ranging in age from 18 to 38 years (M = 22.15, SD = 3.63), with 18 participants being German and nine Dutch. The participants had an average of 4.4 years of driving experience (SD = 3.51) and reported that they drive everyday (14.8%), once per week (14.8%), twice per week (40.7%) and once per month (29.6%). All participants obtained their driving license at least one year prior to the experiment and had never driven or been a passenger in a commercially available automated car. Furthermore, participants had normal vision or corrected-to-normal vision, no motion-sickness during the experiment, no psychological disorders, and no colour vision deficits.

2.2 Apparatus and Materials

The participants completed the study in a fixed-base simulator, consisting of a Playseat Evolution seat with Logitech G29 steering wheel and pedals. During the experiment, participants wore an Oculus Rift VR headset (Oculus, 2017) and an UFI Pneumotrace II (UFI, 2012) respiratory belt transducer (RBT) which was connected via a LabJack U3-LV to the computer. Furthermore, participants galvanic skin response (GSR) was measured with a MySignals developer kit (MySignals, 2019) running on an Arduino platform.

Figure 4

Driving simulator used for the study

For measuring trust and self-identification, two questionnaires were used and distributed via Qualtrics. For assessing trust in the AD vehicle, before and after the experiment, a slightly modified version of the ED trust scale (see Jian et al., 2000) was used. The modified version (see Appendix A) entailed seven statements which were answered on a 7-point Likert scale (1 = not at all; 7 = extremely). The scale had a high level of internal consistency, as determined by a Cronbach's alpha of .90 for the pre-questionnaire and .81 for the post-questionnaire.

Participants' self-identification with the simulated vehicle was assessed by using an adapted version of the Adler et al. (2014) questionnaire. This questionnaire (see Appendix B) entailed eight statements which were answered on a 7-point Likert scale (-3 = totally disagree; 3 = totally agree). Cronbach's alpha for this scale was .83.

2.3 Simulation

The simulation was programmed in Unity by the Dutch engineering solution provider Witteveen + Bos. In the simulation, participants drove the car on an empty motorway without any traffic. For the first three minutes, the car was in manual mode, therefore, participants had to actively drive the car. After the three-minute manual drive, the car prompted the driver to let go of the driving controls, leading to the activation of the automated driving mode. The prompt was indicated by a flashing icon in the instrument cluster (see Figure 5). In the AD mode phase, blue visual feedback patterns were displayed in the car's windshield, side windows, rear window and in the ambient lighting. Therefore, the visual feedback was always visible, also if participants stopped observing the road. In the synchronised condition, the visual pattern pulsated in synchrony with the participants breathing pattern. The intensity of the lights oscillated between a minimum value at the end of the outbreath and a maximum value at the end of the inbreath. In the Async condition, the cockpit lights pulsated in a randomised way that did not synchronise with participants respiration. In the Repetitive condition, cockpit lights pulsated constantly with the same frequency. After 15 minutes, a takeover request (TOR) was indicated via the blue visual feedback lights by means of a rapidly pulsing blue light pattern and a flashing red icon on the instrument cluster. In all three conditions, the TOR disrupted the respective pattern. When the TOR was issued, participants were requested to takeover control within eight seconds, to avoid crashing into a simulated barrier which was placed in the driving lane.

Figure 5

Left: the car in manual mode (icon on instrument cluster shows manual mode; started flashing once AD was available); Middle: the car in automated mode (blue AD mode icon is displayed, and blue visual patterns are active). Right: TOR (icon flashes red, and frequency of blue visual pattern is rapidly increased).

2.4 Design

A between-subject design with three participant groups was employed in this experiment. The three conditions were the independent variable, while reaction time, lateral displacement, trust, self-identification, and skin conductance were dependent variables. Participants were randomly assigned to the conditions and were not told in which condition they performed, until the experiment had been completed.

2.5 Procedure

Participants were welcomed at the laboratory and were handed an FFP-2 face mask. After entering the office, participants were requested to fill in a Covid-19 questionnaire and disinfect their hands. Afterwards, participants were asked to fill in a demographic questionnaire and the pre-assessment of the Trust-ED scale. Following that, participants were informed about the driving scenario and what their task was. Furthermore, two video clips were shown to the participant, showing how the AD mode and the visual patterns looked like, as well as how the TOR was displayed. Once they confirmed that they understood this, participants were asked to attach the respiratory belt transducer below the rib cage at the level of the diaphragm. Once the RBT was attached, participants took place in the simulator seat and were handed the VR headset. GSR sensors were attached to the fingers and a test run was started. This test run took around three to five minutes and helped participants get used to the steering sensitivity and the AD-mode activation. After they indicated that they understood the procedure, the experiment began. Once the experiment ended, participants were helped out of the equipment and were asked to fill in the remaining questionnaires. Finally, the purpose of it was explained, whereby participants were able to ask any remaining questions.

2.6 Data Analysis

All data was explored by creating a descriptive statistics table with mean, standard deviation, maximum and minimum. For reaction time data, an Exgaussian Regression Model was chosen, as reaction times can never be zero. For physiological arousal, a Gaussian Regression Model was used. To analyse the Self-Identification and Trust questionnaire, a Beta-Regression Model was applied. Lastly, lateral displacement was analysed by means of a Gamma-Regression Model. For all analyses, the Repetitive condition was used as reference group. Furthermore, all Generalised Linear Model analyses were conducted with 10.000 iterations.

Results

3.1 Reaction Time

The collected data shows that the average reaction time in the Repetitive condition was 3859 ms (*SD* = 994 ms). Participants in the Sync condition were on average 1050 milliseconds faster than in the Repetitive condition (*M* = 2808 ms, *SD* = 876 ms), while participants in the Async condition were on average 400ms slower (*M* = 4252 ms, *SD* = 1630 ms). For an illustration, see Table 1 and Figure 6.

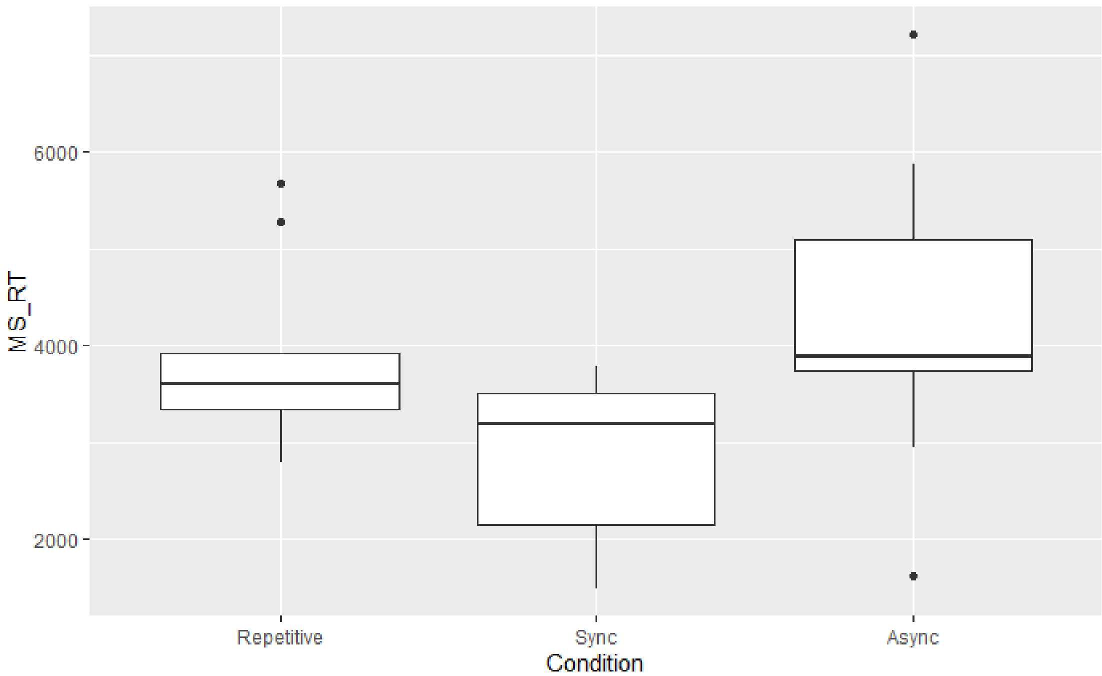
Table 1

Descriptives of Reaction Time across the Conditions.

Condition	Mean RT	SD RT	Max RT	Min RT
Repetitive	3859	994	5678	2790
Sync	2808	876	3782	1491
Async	4252	1630	7210	1623

Figure 6

Boxplot of Reaction Time in Milliseconds Across the Three Conditions.



Given that reaction time data can never have a lower boundary of 0, an Exgaussian Regression model with 10.000 iterations was applied with the Repetitive condition as reference group (see Table 2). The analysis shows that participants in the Repetitive condition had an average reaction time of 3848 ms (95% CI [3108 ms, 4567 ms]). In the Async condition, participants took on average 400 ms (95% CI [-628 ms, 1424 ms]) longer. In the Sync condition, participants took on average 1058 ms (95% CI [-2092 ms, 48 ms]) less than in the repetitive condition. Overall, the credibility interval in all three condition is rather large. This means, that the centre value might not be the true value. Thus, the true value lies within the credibility interval with 95% certainty.

Table 2

Exgaussian Analysis of Reaction Times. Values are in Miliseconds

	Estimates with 95% credibility limits		
Parameter	Center	Lower	Upper
Intercept (Repetitive)	3848.205	3107.553	4566.837
Sync	-1057.544	-2092.214	48.957
Async	400.094	-628.407	1423.982

3.2 Lateral Displacement

Lateral Displacement (LD) data was calculated by subtracting the LD of the takeover request point from the LD of the time-point when the barrier occurred. In the Repetitive condition, participants had on average a displacement of 2.38 (*SD* = 1.59). Participants in the Sync condition had a slightly lower average displacement of 2.06 (*SD* = 1.27), whereas participants in the Async condition had the lowest lateral displacement (*M* =1.88, *SD* = .98). For further information see Table 3 and Figure 7.

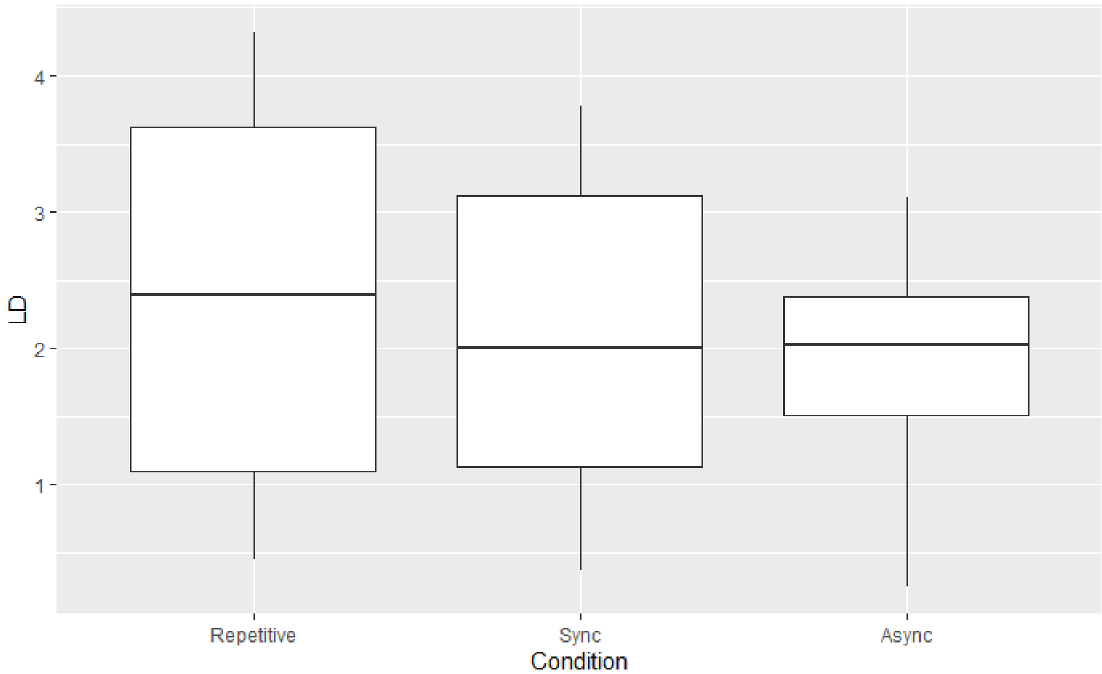
Table 3

Descriptives of Lateral Displacement across the Conditions.

Condition	Mean LD	SD LD	Max LD	Min LD
Repetitive	2.38	1.59	4.32	0.46
Sync	2.06	1.27	3.78	0.37
Async	1.88	0.98	3.10	0.26

Figure 7

Boxplot of Lateral Displacement Data across Conditions.



Furthermore, a Gamma Regression was applied (see Table 4). The analysis shows that participants in the Repetitive condition had an average displacement of .89 (95% CI [.34, 1.61]). Participants in the Sync condition had on average a -.15 (95% CI [-1.02, .67]) smaller displacement than in the reference group. With -.24 (95% CI [-1.15, .66]) less than in the Repetitive group, the participants in the Async condition had the smallest lateral displacement. While the CI for the Repetitive condition is smaller than for the other conditions, the certainty is still not sufficiently good enough to say that the centre value is the true LD value. With 95% certainty, the true values lie between the lower and upper bound.

Table 4

Gamma-Regression of Lateral Displacement.

	Estimates with 95% credibility limits		
Parameter	Center	Lower	Upper
Intercept (Repetitive)	0.8972	0.3401	1.6096
Sync	-0.1506	-1.0174	0.6695
Async	-0.2379	-1.1501	0.6548

3.3 Physiological Arousal

The galvanic skin response data consisted of an averaged eight-minute-long sample which was obtained during the fifth and thirteenth minute of the experiment. During this time, the car was completely in automated mode and participants had no task to complete. The data was standardised to account for individual differences. Two participants had to be excluded, due to malfunctioning equipment during the experiment. In the Repetitive condition, participants had on average -.244 mS (*SD* = .73 mS). In the Sync condition, physiological arousal was on average .59 mS (*SD* = 1.21 mS), while participants in the Async condition, had on average -.30 mS (*SD* = .87 mS). For an illustration see Table 5 and Figure 8.

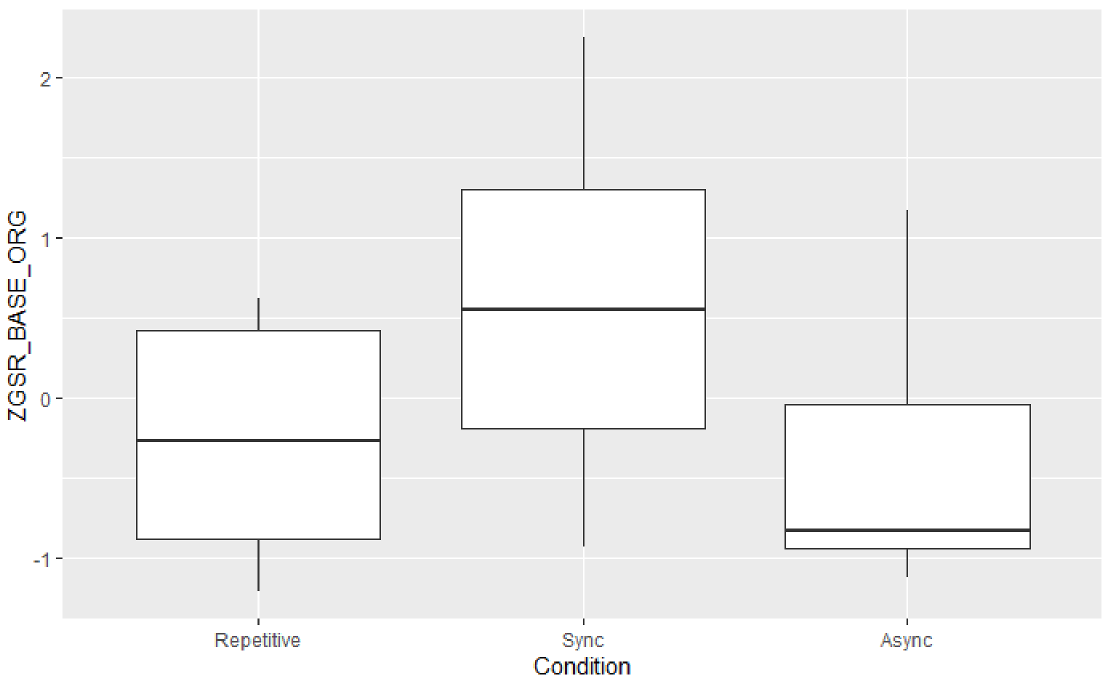
Table 5

Descriptives of Physiological Arousal Data across the Conditions. Values are standardised and in Millisievert.

Condition	Mean GSR	SD GSR	Max GSR	Min GSR
Repetitive	-.244	.728	.612	-1.210
Sync	.585	1.205	2.244	-.937
Async	-.303	.871	1.169	-1.118

Figure 8

Physiological Arousal across the conditions. Values are standardised.



For the Analysis, a Gaussian Regression model was applied with the Repetitive condition as reference group (see Table 6). The analysis shows that participants in the Repetitive condition had an average arousal of -.242 mS (95% CI [-.974 mS, .457 mS]). In the Async Condition, participants were -.055 mS (95% CI [-1.046 mS, .902 mS]) less aroused than in the reference group. Contrary to our expectations, participants in the Sync condition had the highest physiological arousal, with .826 mS (95% CI [-.176 mS, 1.848 mS] more than in the Repetitive condition. In all three conditions, the credibility interval is rather larger, meaning that we cannot be certain that the centre value is the actual true value. The true value thus lies between the lower and upper limit.

Table 6

Gaussian Regression Analysis of Physiological Arousal. Values are Standardised.

	Estimates with 95% credibility limits		
Parameter	Center	Lower	Upper
Intercept (Repetitive)	-0.2418735	-0.9735917	0.4570540
Sync	0.8260743	-0.1760636	1.8476439
Async	-0.0554229	-1.0461306	0.9024704

3.4 Self-Identification Questionnaire

Self-Identification was measured on a 7-point Likert scale. The collected data shows that in the Repetitive condition, participants had an average Self-ID of 3.38 (SD = 1.08), while participants in the Async condition had a slightly higher Self-ID of 3.40 (SD = 0.91). The lowest Self-ID was found in the Sync condition (M = 3.29, SD = 1.27). For further information see Table 7 and Figure 9.

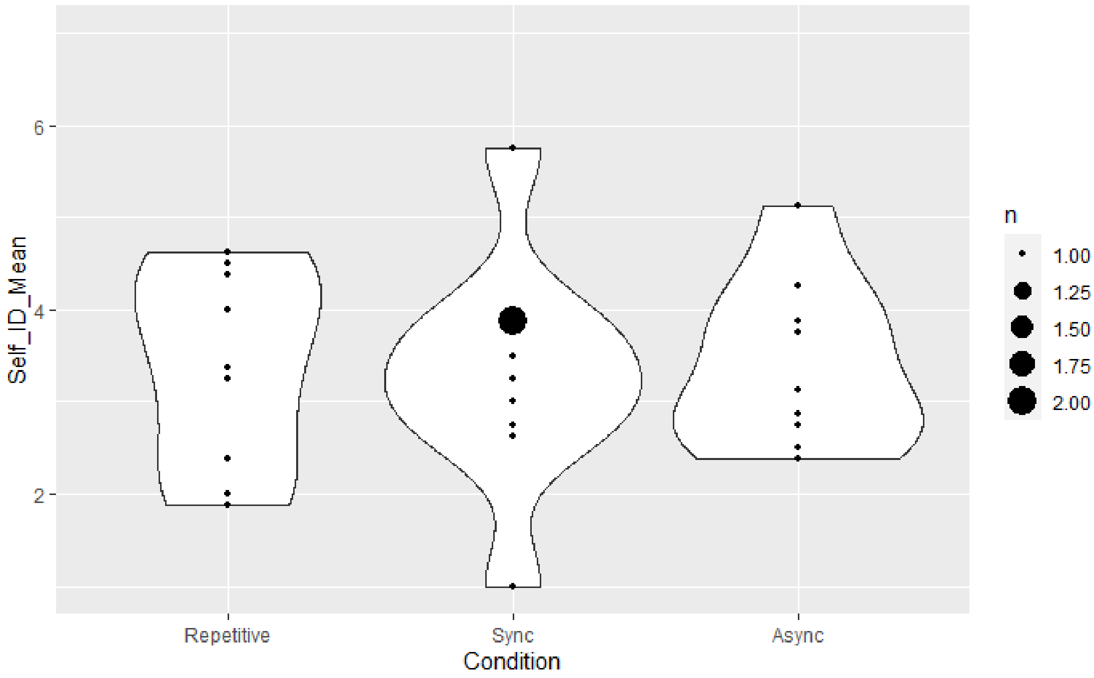
Table 7

Descriptives of Self-ID Data across the Conditions.

Condition	Mean Self-ID	SD Self-ID	Max Self-ID	Min Self-ID
Repetitive	3.375000	1.0825318	4.625	1.875
Sync	3.291667	1.2670709	5.750	1.000
Async	3.402778	0.9138213	5.125	2.375

Figure 9

Violin Plot of Self-Identification Scores Across the Three Conditions



Further analysis was conducted, and a Beta-Regression model was applied (see Table 8). As this model requires responses between 0 and 1, the Self-ID scores were normalised by adding a small value (0.001) and dividing it by 7.002. The analysis suggests that participants in the Repetitive condition had a Self-ID score of, on average, -.0738 (95%CI [-.5055, .3598]). Participants in the Async condition had with a .0249 (95% CI [-.6623, .5627]) higher score, a slightly higher Self-Identification with the vehicle, than participants in the Repetitive condition. Participants in the Sync condition had a -.0517 (95% CI [-.6623, .5627] lower Self-Identification score, and therefore, the lowest self-identification with the simulated vehicle. As the credibility intervals are much larger, we cannot be certain that average Self-ID scores are the true scores. The true value thus, lies within the credibility interval with 95% certainty.

Table 8

Beta-Regression of Self-Identification Scores. Values are normalised.

	Estimates with 95% credibility limits		
Parameter	Center	Lower	Upper
Intercept (Repetitive)	-0.07375031	-0.5055261	0.3598075
Sync	-0.05166043	-0.6623490	0.5626613
Async	0.02489133	-0.5904457	0.6349177

3.5 Trust Questionnaire

Trust was measured on a 7-point Likert scale before the experiment and directly afterwards. Participants in the Repetitive condition had an average of 4.06 (*SD* = .60) before the experiment and 5.01 (*SD* = .94) after. In the Async condition, participants had an average of 4.16 (*SD* = 1.30) before the experiment and 5.29 (*SD* = .79) after. Contrary to our expectations, participants in the Sync condition had the highest trust score before the experiment across all conditions (*M* = 4.41, *SD* = 1.35) but the lowest one after the experiment (*M* = 4.57, *SD* = 1.03). Trust did increase by one point in the Repetitive and the Async condition, while only a marginal improvement was found in the Sync condition. See Table 9 and Figure 1 for a comparison between pre- and post-measurements.

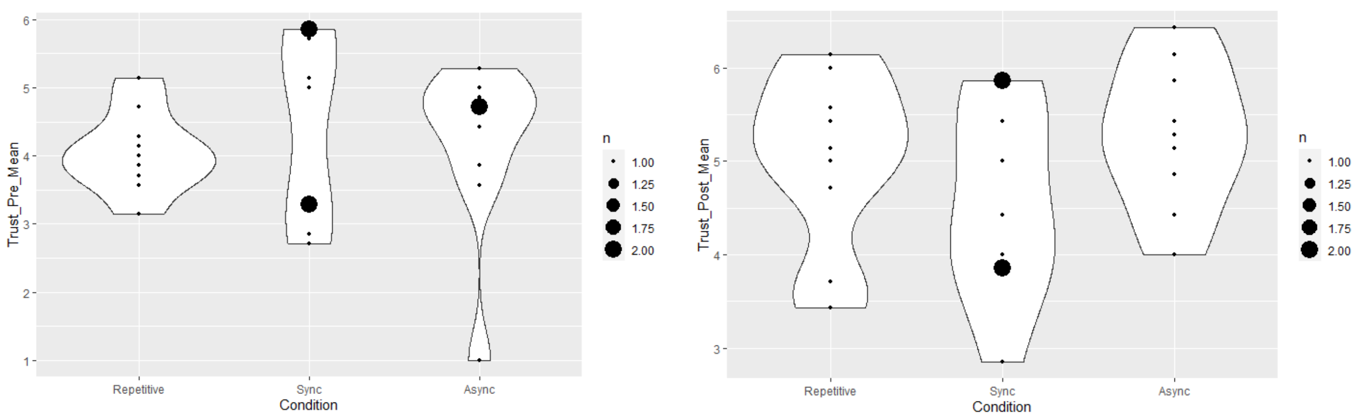
Table 9

Descriptives of Trust Scores for Pre-and Post-Measurement across Conditions.

Condition	Mean		SD		Max		Min	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Repetitive	4.06	5.02	0.60	0.94	5.14	6.14	3.14	3.43
Sync	4.41	4.57	1.35	1.03	5.86	5.86	2.71	2.86
Async	4.16	5.29	1.30	0.79	5.29	6.43	1.00	4.00

Figure 10

Violin Plot for Pre- and Post-Measurements of Trust Scores. Pre-Measurement is shown in the Left Plot.



Furthermore, Trust scores were normalised and the difference between Pre- and Post-measurement was calculated. The difference-value was then used for a Beta-Regression (see Table 10). The analysis shows that participants in the Repetitive condition had an average difference of .54 (95% CI [.24, .87], whereas participants in the Async condition had a .17 (95% CI [-.28, .61]) higher trust difference than participants in the Repetitive condition, while participants in the Sync condition had a -.46 (95 % CI [-.90, .02]) lower trust difference. The credibility interval is fairly small; thus, we can state that the centre value is a good approximation on where the true value is located.

Table 10

Beta-Regression of Trust-Score Difference between Pre- and Post-Measurement. Values are normalised.

	Estimates with 95% credibility limits		
Parameter	Center	Lower	Upper
Intercept (Repetitive)	0.5430	0.2377	0.8660
Sync	-0.4612	-0.9013	-0.0240
Async	0.1727	-0.2808	0.6192

Discussion

In this study, we investigated whether drivers' representation of peripersonal space could be modified by visuo-respiratory synchronisation, to improve takeover performance in Level 3 automated vehicles. We assumed that visuo-respiratory synchronisation during automated driving would lead to an extension of PPS, and a sudden disruption of the visual pattern would lead to faster reaction times when a TOR is issued. Furthermore, we investigated whether lateral displacement of the vehicle would be smaller in the Sync condition. To gain further insights into the subject, we investigated whether physiological arousal would be lower, and self-identification and trust would be higher in the Sync condition. To the best of our knowledge, this is the first study investigating the benefits of extended multisensory space during automated driving.

4.1 Main Findings

Regarding the first hypothesis whether reaction times are lower in the Sync condition, we found that in our observed sample, participants in the Sync condition reacted around one second faster than controls. Further analysis, however, suggested that these findings should be taken with caution, as the credibility interval was rather large.

For the second hypothesis, that lateral displacement would be lower in the Sync condition, we found that participants in the Async condition had the lowest displacement. Here, as well, further analysis showed that the credibility interval was too large to certainly state that lateral displacement would be affected by the manipulations.

For the third hypothesis that physiological arousal would be lowest in the Sync condition, we found that in our observed sample, participants in the Sync condition were way more aroused than participants in the control conditions. For making certain statements about this effect, further analysis showed that the credibility interval was too large to draw strong conclusions.

For the fourth hypothesis, that self-identification would be higher in the Sync condition, we found that participants in the Sync condition had the lowest self-identification with the vehicle. Even though this is consistent with findings by Adler et al. (2014), further analysis suggests that the true self-identification value lies within a rather larger credibility interval. Therefore, no strong conclusion can be drawn from our study about the effect on self-identification.

Lastly, for the fifth hypothesis, that trust would be higher in the Sync condition, we found that trust only marginally improved in the experimental condition. A higher improvement was found in the control conditions. Further analysis showed that this effect is possibly present, as the credibility interval was fairly small. Thus, we can state that visuo-respiratory synchronisation, in our case, did not lead to a higher trust in the automated vehicle.

4.2 Implications

As automated driving technology rapidly advances, new methods of human-vehicle interaction are needed. We believe that a multidisciplinary approach would be well suited to find solutions for new designs, to improve takeover performance and safer interaction with the vehicle. Even though we did not find strong enough results to support claims about a possible effect, it might be conceivable that drivers' PPS extension could help facilitate takeover performance and thus increase safety.

Technically, measuring breathing could be easily integrated by sensors in the seatbelt or seats. Also, a majority of car manufacturers already implement ambient lightning in their car's dashboard and door panels. Given that this technology is readily available, implementation of the study design is feasible without major difficulties.

Interestingly, a collaboration between an American artist, a Hyundai Engineer and the Los Angeles County Museum of Art produced a car, termed "roadable synapse". In this vehicle, based on a Hyundai Ioniq, multisensory outputs inside the vehicle are synchronised with the vehicles' telemetry data. For example, the radio music's rhythm gets faster as the car accelerates, and music volume increases when engine RPM increase (Said, 2017). Also, the driver of the car is said to be in a "synchronised hybrid state", where the car is giving constant feedback, leading to increased awareness (Said, 2017). While our study investigated the synchronisation of in-vehicle feedback with drivers' interoceptive cues, the "roadable synapse" uses the "interoceptive" (telemetry) data of the car itself as input for in-vehicle feedback. In line with our study, this might also enhance human-vehicle interaction.

4.3 Limitations

This study has several limitations. First, the statistical power of the experiment is rather low. As we deployed a between-subject design, we cannot rule out the influence of individual differences. Also, whereby other studies found some of the hypothesised effects (e.g., faster reaction times) our study was not able to find these effects with high certainty. Second, when the TOR was issued, the visual pattern rapidly flashed in the same colours as the visual pattern during AD. This might have confused participants, as they did not immediately recognise the flashing pattern as the TOR. Indicating the TOR in another colour would help avoiding confusion. Third, for the design to be effective, participants would need to constantly have their eyes open. As the simulated drive was very monotonous, we cannot exclude the possibility that some participants had their eyes closed during the experiment. Fourth, a video of the TO-procedure was shown to the participants. In this video, the simulated construction site with cones and the barrier was depicted. As there was no other, similar construction site during the simulated drive, attentive participants might have been prepared for the TO. Lastly, the study was conducted during the COVID-19 pandemic, which prevented conducting the experiment with more participants. The sample size consisted solely of students with little driving experience.

4.4 Future Research

First, it is advised that for a replication of this study, a within-subject design should be employed. This would increase statistical power, rule out individual differences, and it would be possible to investigate participant-level effects regarding the manipulation.
Our research exclusively focused on visuo-respiratory effects. In line with other studies, other combinations e.g., cardio-visual synchronisation (Aspell et al., 2013; Heydrich et al., 2018), might facilitate even better results. Further research should also consider a more diverse and larger sample, which would help in drawing stronger conclusions of our observed effects.

Furthermore, following studies with visuo-respiratory synchronisation could also include situational awareness measurements, e.g.by using the SAGAT questionnaire by Endsley (2000). Mindfulness through breathing awareness is a tool often used in positive clinical psychology which is proven to improve situational awareness (Chmielewski et al., 2021; Crundall et al., 2019). Kass et al. (2011) found that mindfulness may improve drivers' awareness of their environment. Through visuo-respiratory synchronisation, drivers could be advised to focus on the visual feedback pattern and thus increase situational awareness.

Conclusion

In this study, we did not find certain enough evidence to suggest that visuo-respiratory synchronisation could facilitate faster and safer responses to takeover requests in Level 3 automated driving. However, we theorise that a possible replication with a different design and a larger sample size could help find stronger evidence to draw final conclusions.

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Appendix A

ED Trust Scale

I am cautious about self-driving cars

1 - not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

Self-driving cars are reliable

1 -not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

I would entrust my car to self-driving functions for lane keeping, lane changing, alerts following object recognition, etc

1 - not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

I can count on self-driving cars

1 - not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

Self-driving cars can have harmful consequences

1 - not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

I trust self-driving cars

1 - not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

I assume that self-driving cars will work properly

1 - not at all	2	3	4	5	6	7 - extremely
○	○	○	○	○	○	○

Appendix B

Self-Identification Questionnaire

Q1 - It seemed as if I was feeling my respiration in the virtual object

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

Q2 - It seemed as if the flashing was my respiration

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

Q3 - It seemed as if the self-driving car was using my lungs to breathe

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

Q4 - I felt as if the self-driving car was breathing with me

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

Q5 - I felt as if the virtual car was my body

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

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Q6 - I felt as if my real body was drifting towards the virtual car

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

Q7 - I felt as if the windshield of the self-driving car was drifting towards my real body

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○

Q8 - It seemed as if I had two bodies

-3 = totally disagree	-2	-1	0	1	2	3 = totally agree
○	○	○	○	○	○	○