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Effects of Automation and Fatigue on Drivers from Various Age Groups

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Abstract: This study explores how drivers are affected by automation when driving in rested and fatigued conditions. Eighty-nine drivers (45 females, 44 males) aged between 20 and 85 years attended driving experiments on separate days, once in a rested and once in a fatigued condition, in a counterbalanced order. The results show an overall effect of automation to significantly reduce drivers' workload and effort. The automation had different effects, depending on the drivers' conditions. Differences between the manual and automated mode were larger for the perceived time pressure and effort in the fatigued condition as compared to the rested condition. Frustration was higher during manual driving when fatigued, but also higher during automated driving when rested. Subjective fatigue and the percentage of eye closure (PERCLOS) were higher in the automated mode compared to manual driving mode. PERCLOS differences between the automated and manual mode were higher in the fatigued condition than in the rested condition. There was a significant interaction effect of age and automation on drivers' PERCLOS. These results are important for the development of driver-centered automation because they show different benefits for drivers of different ages, depending on their condition (fatigued or rested).

Keywords: driver; partial automation; fatigue; age; gender; workload; PERCLOS; reaction time

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1. Introduction

1.1. Motivation

According to recent reports, driver drowsiness is one of the major causes of traffic accidents [1], thus research on driver drowsiness in manual and automated driving is important for road safety. The National Highway Traffic Safety Administration (NHTSA) has announced that 72,000 drowsiness-related car accidents were reported by police from 2009 to 2013 [2]. The American Automobile Association (AAA) has also reported that 40% of the drivers that participated in a study admitted to falling asleep while driving at least once in their life, whereas 27% of them fell asleep in the previous month [3]. Dingus et al. [4] have also reported that about 22–24% of car crashes or near-crashes are related to the drivers' drowsiness.

In addition to the impairing influence of drowsiness in manual driving, monitoring the drivers' state and their ability to control the car is one of the main requirements of the third level of automated vehicles [5]. At this automated level, the driver will still be responsible for the car's performance and they should act safely and promptly in case of automated system faults or complex traffic scenarios [6,7]. Notwithstanding research findings [8] showing that learning can interact with fatigue, leading to shorter reaction times, most previous studies demonstrated that drowsiness has a significant influence to increase drivers' reaction time for braking or steering maneuvers in risky situations to prevent accidents [9–11]. It may not be safe to hand over the car's control to the drowsy drivers in automated cars which can increase the risk of accidents.

1.2. Effects of Human Factors in Driver Drowsiness

1.2.1. Effects of Automation, Age, and Gender

Multiple benefits are considered to emerge from driving automation such as reducing drivers' workload and improving the safety and efficiency of road transportation [12,13]. A reduction in the cognitive and physical workload associated with a driving task is considered to reduce drivers' effort and make driving less prone to errors [14,15]. Research has been dedicated to adapting the level of automation to the level of the operator's workload and avoiding both, a too high and a too low effort [16–19]. When the workload becomes too low, the driving performance is also expected to decrease because drivers may become disengaged from the task. Thus, driving automation can also potentially reduce drivers' situational awareness [12]. There is a relationship between workload and fatigue, meaning that high workload is a predictor of increased fatigue [20].

Research shows significant interaction effects of drivers' age and gender in relation to automation (see for example [21–23]). An assessment of the autonomous emergency braking (AEB) system on a test-driving area using a pedestrian-dummy as a trigger showed that female drivers perceive the AEB braking as being less safe than men did [24,25]. This effect was confirmed by simulated driving tests [21].

An assessment with the Adaptive Cruise Control (ACC) on the road showed significant gender differences in the estimation of the gap between vehicles, perceived usability, and comfort when driving with the ACC [25]. Drivers with an age of 60–75 years selected a slower ACC speed than the drivers in their 20s and 30s [22]. Additionally, drivers with an age of 40–49 years selected a slower ACC speed than those aged 30–39 years [22]. The same study also shows that automation influences drivers' perceived workload and this effect is mediated by drivers' age. Muslim et al. [23] investigated age and gender differences in interacting with an automated driving system (ADS) with four distinct levels of automation: The system could only keep the lane and continue automated driving at a slow speed (20 km/h) (ADS-level 1), or the system requested the driver to take over the vehicle control and change lanes manually (ADS-level 2), or the system requested the driver's permission to execute the lane-change maneuver automatically (ADS-level 3) or the system informed the driver that an automatic lane-change maneuver will start in 6 s and the driver could veto the maneuver execution (ADS-level 4). Muslim et al. [23] found significant effects of the level of automation, gender, and age on drivers' reaction time. Younger female drivers had longer RT than older female drivers when using ADS-3, and longer RT than younger males when driving with ADS-4.

Given the potential benefits of automation for drivers, and for the safety and efficiency of road transportation, it is necessary to consider the age and gender aspects when designing and assessing automated systems.

1.2.2. Effects of Fatigue, Age, and Gender

In a survey study with 1000 Australian drivers, Obst et al. [26] found that 80% of drivers across all age and gender groups drove when sleepy. In addition, many drivers reported that they frequently drove when sleepy, despite being aware of the risks. Most frequently, young to middle-aged drivers and male drivers reported driving while sleepy [26]. Akerstedt and Kecklund [27] studied the influence of age and gender on the risk of being involved in driving accidents. According to their outcomes, the risk of accidents for the young drivers (18–24 years old) is 5 to 10 times higher in the late-night than during the morning. Moreover, the risk of having an accident during the night is two times higher for men than for women. However, Soares et al. [28] reported that male and older drivers are less prone to feel drowsy than other drivers based on the subjective rating of drowsiness using the Karolinska Sleepiness Scale (KSS). The vulnerability of young drivers to sleepiness while driving at nighttime was also studied in [29] using electroencephalogram (EEG) signals to measure the influence of sleepiness on the power of related EEG subbands. This study shows that young drivers can experience extreme levels of sleepiness more rapidly than older drivers during a long drive.

Åkerstedt et al. [30] investigated the effects of driving home from a night shift as compared to a normal shift using a driving simulator. Driving home from the night shift was associated with larger lateral deviation, longer eye closure duration, increased subjective sleepiness, and more frequent incidents as compared to driving after the day shift. In another simulator study, Hargutt et al. [31] showed that drivers' fatigue leads to a loss of attention as indicated by subjective ratings and increased reaction times. Drivers tried to increase speed and, thus, the difficulty of the driving task to regulate their attention [31].

Ahlström et al. [32] studied the influence of partially automated driving (level 2) on fatigue in four different driving tests: daytime-manual, daytime-automated, nighttime-manual, and nighttime-automated. In their study, different sleepiness indicators included subjective ratings on the KSS, blink durations, the PERcentage of eyelid CLOSure (PERCLOS), pupil diameter, heart rate, and recordings of 64 EEG channels. Their results show that the drivers felt more fatigued in the automated tests. The drowsiness effects related to automated driving were stronger during the night as compared to daytime driving tests. In addition, the effect of performing a secondary task (performing a quiz test) on drowsiness during automated driving was studied in [33], where drowsiness in drivers was measured using eyelid movement data. Drivers participated in three different tests: (1) manual driving (no automation), (2) automated driving (hands-off), (3) automated driving, and additionally performing a secondary task. According to the results, the drowsiness index increased in the first and second tests while it remained approximately constant during the third type of tests which highlights the importance of performing a secondary task for keeping the drivers alert during automated driving.

In a review of 10 driver sleepiness studies, Scarpelli et al. [34] concluded that older drivers are less vulnerable to sleep loss and sleepiness-related driving impairments than young adults. For example, Campagne et al. [35] compared the frequency of driving errors and the vigilance of older drivers (60–70 years) and younger drivers (20–30 years and 40–50 years) during long, monotonous night driving sessions in the simulator. They found that driving errors were more frequent in young drivers. Younger drivers also showed a positive correlation between the alpha power of the EEG considered to indicate low vigilance and the number of driving errors. In older drivers, no correlation was found between driving errors and their level of vigilance assessed through the EEG [35]. Lowden et al. [29] also compared young (18–24 years) and older drivers (55–64 years) during simulated morning and evening driving sessions. They found that, although subjective sleepiness scores from the KSS were higher during night driving in both age groups, the younger drivers had higher scores than the older drivers.

Although research shows interdependencies between automation and fatigue [32], automation and workload [12,13], automation and age [23], workload and fatigue [20], workload and age [22], fatigue, age, and gender [27–29], there is a gap in understanding how these variables vary simultaneously. This study aims to address these interactions.

2. Research Questions

This study investigates the effects of automation, drivers' age, gender, and fatigue conditions (e.g., fatigued due to sleep deprivation, extended wakefulness or rested) on drivers' workload, subjective and objective fatigue, and reaction time. In addition, in an exploratory approach, correlations between drivers' age, subjective and objective fatigue, and effort are analyzed for both driving modes (automated and manual) and experimental conditions (fatigued and rested).

3. Materials and Methods

3.1. Participants

Ninety-two drivers volunteered for participation in the study. Data from 3 participants were incomplete. Thus, the data of eighty-nine active drivers (45 females, 44 males) were used in this study. Descriptive data for the age and driving activity of the participants are presented in Table 1. There were no significant differences between the gender and age groups related to the driving activity in the past 12 months. Informed consent was obtained from participants before the experiments, and they received a compensation of EUR 50 after finishing the experiment. The study was conducted according to the ethical guidelines of the Declaration of Helsinki and the General Data Protection Regulation of the European Union. The study protocol was approved by the Ethics Committee of the Medical University of Graz in vote 30–409 ex 17/18 dated 3 August 2018.

Table 1. Age and driving activity of the participants.

Group	**Group Size**	**Age (Years)**		**Driving Activity in the Past 12 Months (Thousand Kilometers)**	
Data	**N**	**Mean**	**SD**	**Mean**	**SD**
Women 20–49 years	23	31.26	10.46	14.043	13.645
Men 20–49 years	18	29.44	9.94	15.244	14.843
Both genders 20–49 years	41	30.46	10.15	14.571	14.015
Women 50–85 years	21	60.29	7.13	13.019	17.449
Men 50–85 years	27	62.52	9.01	17.814	11.021
Both genders 50–85 years	48	61.54	8.23	15.717	14.232
Women total	44	49.29	18.83	16.787	12.591
Men total	45	45.11	17.17	13.554	15.400

3.2. Equipment

This study uses the dataset collected in the WACHSens project which was a collaborative project of these partners: (1) Human Research Institute Weiz, (2) Graz University of Technology, (3) apptec Factum Vienna, and (4) AVL UK. The Automated Driving Simulator of Graz (ADSG) at the Institute of Automotive Engineering (Graz University of Technology) was used to perform the driving tests. The ADSG is shown in Figure 1.

In the ADSG, eight LCD panels simulate the driving track at an angle of 180 degrees. A rear screen is added to the simulator that can be observed in the inner mirror of the car cabin. To improve the immersion feature of the ADSG, the engine, rolling and wind noises were also generated. The vibration of the car chassis and seats were produced by four bass shakers. The haptic feedback of the steering wheel was produced by the Sensodrive™ steering wheel system (https://www.sensodrive.de/, accessed on 9 April 2022). The vehicle dynamic of the car was simulated using the full vehicle software AVL-VSM™ (https://www.avl.com/-/avl-vsm-vehicle-simulation, accessed on 9 April 2022) that also calculates the engine speed and torque for the noise generators. To simulate the automated driving mode in the ADSG, two different driver assistance systems were implemented: (1) Adaptive Cruise Control (ACC) and (2) Lane-Keeping Assist (LKA). The ACC and LKA control the longitudinal and lateral vehicle dynamic during the automated driving tests, respectively. Before the automated tests, the driver only needs to turn on both ACC and LKA using a provided human–machine interface. Thus, the driver gives no input to control the car during the automated test. A "coffee cup" icon appeared three times randomly during the test on the head-up display (HUD). The icon disappeared when the drivers pressed the steering wheel. A pressure-sensitive foil was placed inside the steering wheel that sensed pressure inserted from the driver's hands. Thus, the driver did not need to reach out his hands unless they were grabbing the steering wheel. Our previous studies explain more details of the driving simulator [36,37].

3.3. Dependent and Independent Variables

The workload was self-assessed by the drivers using the NASA Task Load Index [39] with six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration. Each NASA TLX scale ranged from 0 (very low) to 10 (very high). Subjective fatigue was assessed using the Karolinska Sleepiness Scale (KSS) ranging from 1 (very alert) to 9 (very sleepy, effort to stay awake, fighting sleep) [40].

Figure 1. Automated Driving Simulator of Graz (ADSG). During the WACHSens project and to cancel the disturbing noise of the surrounding area and adjust the indoor temperature, ADSG is placed inside an insulating wooden cube. This figure is reprinted from our previous open-access work [38].

The PERCLOS was calculated during driving as the proportion of the cumulative time when the eyes are more than 80% closed during a 1 min interval [41]. For example, if eyes are cumulatively more than 80% closed for 15 s, then the PERCLOS will be equal to $\frac{15}{60}$ or 0.25. If the eyes are never closed more than 80% the PERCLOS will be zero during the corresponding time window and if they are always more than 80% closed the PERCLOS will be 1. Previous studies show that PERCLOS is an accurate indicator of driver sleepiness [42,43]. In addition, the reaction time (RT) of the drivers to a "coffee cup" icon that appeared at three random times on the head-up display (HUD) was recorded and analyzed. The icon disappeared when the drivers pressed the steering wheel.

Independent variables were the condition of the driver (fatigued versus rested), the driving mode (manual versus automated), and the participant's age and gender. Each participant attended driving experiments on two days, once in a rested and once in a fatigued condition, in a counterbalanced order to avoid the order of presentation artifacts. Counterbalancing means that the participant samples (age and gender groups) were divided in half, with one half completing the two conditions (fatigued versus rested; manual versus automated driving) in one order and the other half completing the conditions in the reverse order. In the fatigued condition, the drivers were either in a state of extended wakefulness (16 h awake) or sleep deprivation (4 h sleep in the previous night). Generally, adults need between 7 and 9 h of sleep per night [44].

During each test day, the participants drove for 30 min on a motorway in each, an automated and a manual mode, in a counterbalanced order. In the automated driving mode, the drivers used the Adaptive Cruise Control and Lane-Keeping Assist.

3.4. Experimental Procedure

The drivers were instructed to drive according to rules and regulations. Each participant received a familiarization session with the driving simulator and practiced the reaction prompted by the coffee cup icon. The participants were instructed to react fast to the coffee cup icon that was randomly displayed during driving. Before the test, the participants filled out the KSS questionnaire that was used as a baseline. After the driving test, the participants filled out the NASA-TLX and KSS questionnaires.

3.5. Data Analysis

Repeated-measures analysis of variance was calculated for analyzing the effects of automation, condition, gender, and age. There were two within-subjects factors: condition (with two levels fatigued and rested) and driving mode (manual and automated). There were two between-subjects factors: gender (female and male) and age group (20–49 years and 50–85 years). Data transformation by $ln(x+1)$ was used before calculating the ANOVA. In addition, non-parametric coefficients of correlations have been calculated using the raw data. For the statistical tests, alpha was set at 0.05.

4. Results

4.1. Automation Effects on Drivers' Workload

The results show significant effects of the driving mode on the mental demand [F(1,85) = 53.54, $p < 0.0001$, $\eta^2 = 0.39$], physical demand [F(1,85) = 56.14, $p < 0.0001$, $\eta^2 = 0.40$], temporal demand [F(1,85) = 42.28, $p < 0.0001$, $\eta^2 = 0.33$], performance [F(1,85) = 46.21, $p < 0.0001$, $\eta^2 = 0.35$], and effort [F(1,85) = 53.07, $p < 0.0001$, $\eta^2 = 0.38$], as rated by the drivers. Frustration was not significantly influenced by the driving mode. As Table 2 shows, the drivers perceived a lower workload and performance during automated driving as compared to manual driving. In the supplementary information, Table S1 presents the mean and standard deviation of drivers' workload for different age and gender groups.

Table 2. Workload, PERCLOS, and reaction time (RT) in automated and manual modes.

Driving Mode	Automated Driving		Manual Driving	
Dependent Measure	**Mean**	**SD**	**Mean**	**SD**
Mental Demand	0.950	0.062	1.373	0.060
Physical Demand	0.670	0.060	1.130	0.055
Temporal Demand	0.709	0.058	1.038	0.060
Performance	1.343	0.076	1.747	0.046
Effort	1.047	0.071	1.494	0.058
Frustration	1.221	0.075	1.220	0.068
Minimal PERCLOS	0.008	0.002	0.005	0.001
Maximal PERCLOS	0.198	0.014	0.133	0.010
Median PERCLOS	0.050	0.007	0.025	0.004
Mean PERCLOS	0.062	0.007	0.034	0.004
Variance PERCLOS	0.005	0.001	0.003	0.001
Minimal RT	0.940	0.043	0.814	0.038
Maximal RT	1.322	0.084	1.101	0.058
Median RT	1.083	0.055	0.932	0.040
Mean RT	1.154	0.066	0.970	0.046
Variance RT	0.626	0.167	0.352	0.105

As illustrated in Figure 2, the interaction term between condition and automation was significant for drivers' perceived temporal demand (time pressure) [F(1,85) = 12.01, $p < 0.001$, $\eta^2 = 0.12$], effort F[(1,85) = 3.96, $p < 0.05$, $\eta^2 = 0.05$], and frustration [F(1,85) = 9.14, $p < 0.003$, $\eta^2 = 0.10$]. The effects on mental demand, physical demand, and perceived performance did not reach statistical significance and are not illustrated. Temporal demand was significantly affected by drivers' age [F(1,85) = 5.04, $p < 0.03$, $\eta^2 = 0.06$]. Subjective time pressure was lower in the age group 20–49 (M = 0.754, SD = 0.078) as compared to the age group 50–85 (M = 0.994, SD = 0.073). Other workload aspects were not significantly affected by age. The interaction term age*gender did not reach statistical significance.

4.2. Automation Effects on Drivers' PERCLOS

As Table 2 shows, all parameters of drivers' PERCLOS were lower in manual as compared to automated driving, which also means less fatigue, since PERCLOS is an accepted indicator. These differences reached statistical significance [minimum PERCLOS F(1,71) = 5.08, $p < 0.03$, $\eta^2 = 0.07$; maximum PERCLOS F(1,71) = 25.56, $p < 0.0001$, $\eta^2 = 0.30$;

median PERCLOS $F(1,71) = 21.76$, $p < 0.0001$, $\eta^2 = 0.23$; mean PERCLOS $F(1,71) = 26.46$, $p < 0.0001$, $\eta^2 = 0.27$ and PERCLOS variance $F(1,71) = 6.76$, $p < 0.01$, $\eta^2 = 0.08$].

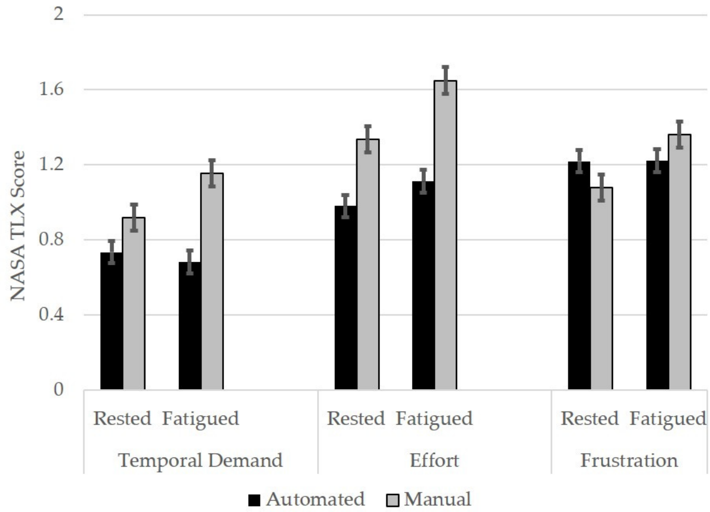

Figure 2. Effects of automation on drivers' workload in rested and fatigued conditions. Error bars indicate SD.

As illustrated in Figure 3, the interaction term condition between and automation was significant for drivers' mean, median, and maximum PERCLOS [mean PERCLOS $F(1,71) = 8.43$, $p < 0.005$, $\eta^2 = 0.11$; median PERCLOS $F(1,71) = 7.21$, $p < 0.009$, $\eta^2 = 0.09$ and maximum PERCLOS $F(1,71) = 7.21$, $p < 0.009$, $\eta^2 = 0.09$]. The effects on minimum PERCLOS and variance PERCLOS did not reach statistical significance. In the supplementary information, Table S2 presents the mean and standard deviation of drivers' PERCLOS for different age and gender groups.

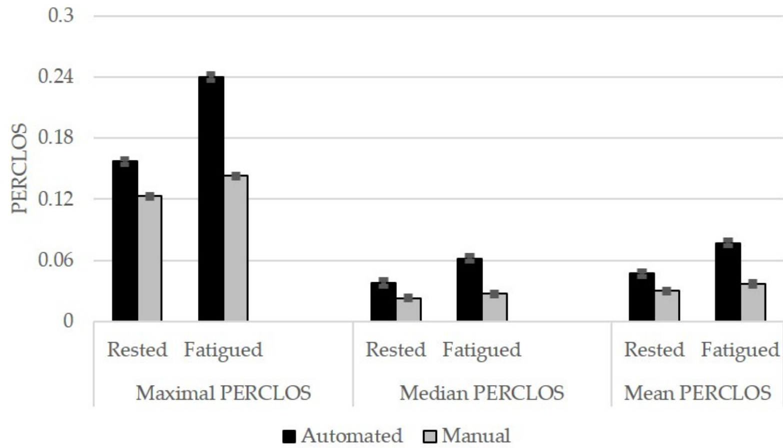

Figure 3. Effects of automation on drivers' PERCLOS in rested and fatigued conditions. Error bars indicate SD.

4.3. Automation Effects on Drivers' Subjective Fatigue

The analysis of KSS ratings shows that drivers felt significantly more fatigued after driving in the automated mode [Mean = 1.895, SD = 0.032] and manual mode [Mean = 1.85, SD = 0.032], as compared to the baseline values before the tests [Mean = 1.561, SD = 0.03], [$F(2,170) = 81.74$, $p < 0.0001$, $\eta^2 = 0.49$]. The interaction term condition and automation was also significant [$F(2,170) = 15.39$, $p < 0.0001$, $\eta^2 = 0.15$], (see also Figure 4). As illustrated in Figure 4, the baseline KSS was higher in the fatigued as compared to the rested condition, because the drivers were already fatigued when they started the experiment. This was expected if the participants followed the instruction for the fatigued part of the experiment. In the supplementary information, Table S3 presents the mean and standard deviation of drivers' KSS scores for different age and gender groups.

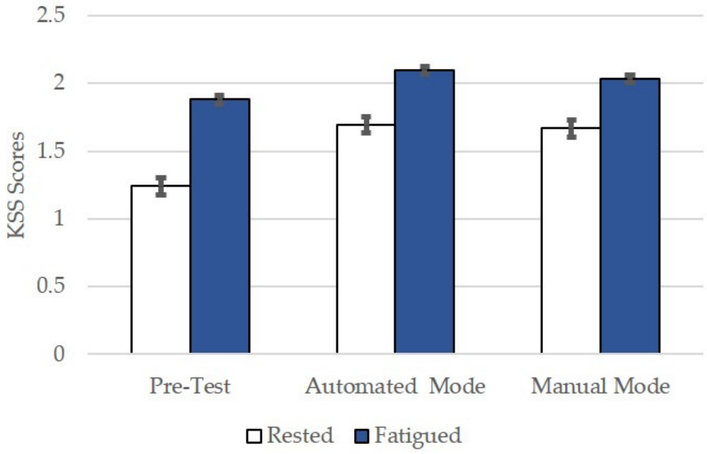

Figure 4. Subjective fatigue scores in different conditions and driving modes. Error bars indicate SD.

4.4. Automation Effects on Drivers' Reaction Time

Driving automation slowed down the reaction time (RT) of drivers to icons that appeared at random intervals on the head-up display during driving (see Table 2). This effect was significant for various parameters [minimum RT $F(1,44) = 13.73$, $p < 0.001$, $\eta^2 = 0.24$; maximum RT $F(1,44) = 7.79$, $p < 0.008$, $\eta^2 = 0.15$; median RT $F(1,44) = 18.28$, $p < 0.0001$, $\eta^2 = 0.29$; mean RT $F(1,44) = 11.49$, $p < 0.001$, $\eta^2 = 0.21$], except the RT variance. The interaction term between automation and condition did not reach significance for the RT. In the supplementary information, Table S4 presents the mean and standard deviation of drivers' reaction time for different age and gender groups.

4.5. Effects of Drivers' Age and Gender

Interaction terms automation–gender and the automation–age group did not have a statistically significant effect on drivers' workload, their reaction time to the icons on the head-up-display, or the subjective fatigue scores on the KSS. The interaction term between automation and age group had a significant effect on maximum PERCLOS [$F(1,71) = 5.24$, $p < 0.025$, $\eta^2 = 0.069$], with differences in PERCLOS between automated and manual mode being larger in the age group 20–49 years as compared to the group 50–85 years (see Figure 5). Effects of age, gender, or fatigue condition did not significantly influence drivers' reaction time. In the supplementary information, Tables S1–S4 present the mean and standard deviation of drivers' workload, PERCLOS, KSS, and reaction time for different age and gender groups, respectively.

4.6. Correlations between Age, Effort, and Fatigue

In addition, correlations between subjective effort, subjective fatigue, age, and different PERCLOS parameters have been calculated. The details of these correlations are presented in Table S5 of the supplementary information. The results show a significant positive correlation between the scores of subjective effort and fatigue related to automated driving in the rested (Rho = 0.428, $p < 0.0001$, N = 89) and fatigued condition (Rho = 0.288, $p < 0.003$, N = 89). Similarly, there were significant positive correlations between the scores of subjective effort and fatigue related to manual driving in the rested (Rho = 0.439, $p < 0.0001$, N = 89) and fatigued condition (Rho = 0.432, $p < 0.0001$, N = 89). When driving with automation in the rested condition, only correlations between subjective fatigue and minimum PERCLOS reached statistical significance. In the fatigued condition, there were significant correlations between subjective fatigue and maximum, median, mean PERCLOS, and PERCLOS variance both in the automated and manual driving modes. In the fatigued condition, age correlates negatively with the maximum, median, mean PERCLOS, and PERCLOS variance when driving with automation. Similarly, when driving manually in the fatigued condition, age correlates negatively with the maximum PERCLOS and PERCLOS variance.

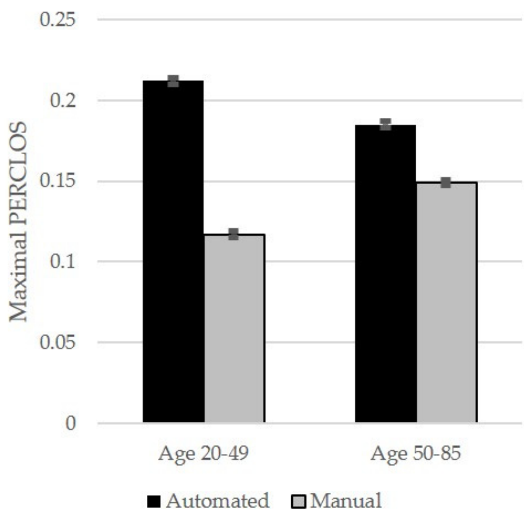

Figure 5. Driving automation had different effects in various age groups. Error bars indicate SD.

5. Discussion

Research shows that driver drowsiness is one of the major causes of traffic accidents [1]. This explorative study aimed to investigate how drivers are affected by automation when driving in rested and fatigued conditions. Overall, the results show a positive effect of automation to significantly reduce drivers' perceived workload and effort, confirming the findings of previous works in [12–14]. Nevertheless, the results of this study show that automation has different effects, depending on if the drivers are rested or fatigued. The temporal demand experienced by drivers and their effort was higher in the manual mode than in the automated mode, and these differences were larger when fatigued as compared to the rested condition. An inverse effect was observed for frustration. This was similar in both conditions when driving automation was used. However, in manual driving mode frustration was higher when drivers were in a fatigued state as compared to the rested condition. The higher subjective effort was associated with higher subjective fatigue in both driving modes, automated and manual.

Despite positive effects to reduce drivers' workload and effort, driving automation that releases the human from steering and speed control as used in this study, also increases drivers' drowsiness, meaning that drivers can be less vigilant and prepared to react. Although high effort is a known contributor to fatigue, decreasing drivers' effort under a certain level can have a negative effect [15,44]. The results also show that during automated driving, drivers' subjective fatigue, the percentage of eye closure (PERCLOS), and reaction times were also higher as compared to manual driving. The PERCLOS was higher in the automated mode than in manual mode, and these differences were larger when fatigued as compared to the rested condition. Although the reaction to the icon is different from taking over the control of a vehicle, a similar delay could be inferred for take-over. The slower reaction time in the automated mode as compared to manual mode needs to be considered in the design of the human–machine interaction for the third level of automated vehicles [5]. At level three, the driver is expected to act safely and promptly in case of automated system faults or complex traffic scenarios [6,7]. For this, a longer handover time is recommended.

As expected, in the fatigued condition, higher fatigue scores were associated with higher values of the maximum, median, mean PERCLOS, and PERCLOS variance in both driving modes. However, drivers' age added interesting effects. In the age group 50–85 years, the maximal PERCLOS was higher than in the age group 20–49 years when driving manually. Nevertheless, in the age group 50–85 years, the maximal PERCLOS was lower than in the age group 20–49 years when using automation. The automation eliminates the physical load associated with the driving task and resources can focus on monitoring. Thus, this effect is particularly beneficial for drivers from the older age group, as demonstrated by the positive effect of automation to reduce drivers' PERCLOS. As the results show, older age was associated with lower values of the maximum, median, mean PERCLOS, and PERCLOS variance during automated driving in the fatigued condition. In addition, older age was associated with lower values of the maximum PERCLOS and PERCLOS variance also during manual driving in the fatigued condition. This is well in line with the findings that older drivers are less vulnerable to sleep loss than young adults [27,32,33], and older drivers are less prone to become drowsy [28]. In the rested condition, these correlations between age and PERCLOS did not reach statistical significance, probably because this relationship manifests only in a fatigued state. However, more research is needed to clarify this finding. The younger drivers seem to be more alert when the task load is higher (e.g., manual mode). This interpretation could be supported by previous findings showing that drivers tried to increase speed and, thus, the difficulty of the driving task to improve their alertness in a fatigued state [28]. Nevertheless, when interpreting these results in combination with the negative correlation between age and subjective fatigue when driving fatigued in both manual and automated modes, the question arises if age is the sole cause of this effect, or if lifestyles also play a role. This aspect needs further investigation and could be addressed in future studies. Although gender effects did not reach statistical significance, it is a recommended good practice to apply a gender-relevant methodology and address possible gender-specific needs and preferences in research [21,22,45].

These results are important because they show emergent effects and interdependencies of automation, fatigue, task demand, and effort. In addition, these results show how automation affects drivers of different ages when driving in both fatigued and rested conditions. Understanding drivers' subjective experience and reactions are essential for the development of driver-centered automation. Monitoring drivers' state and their ability to control the car is one of the main requirements of the third level of automated vehicles [5]. Our results show that a slower reaction time needs to be accounted for in developing systems for the third level of automation. At this level, the driver is expected to take over the control of the vehicle in complex traffic scenarios or cases of automation failures [6,7]. In addition, the results of this study show that drivers' age and condition (e.g., fatigue) are variables that will also need consideration in the development of adaptive automation. Thus, the scope of adaptive automation research focusing on workload and effort [16–19] could be enlarged to include other variables such as age and drowsiness state.

It was not possible to collect a dataset from drivers of all of all ages in this study, thus the analysis is limited to two broader age groups (20–49 and 50–85 years). There is no consensus yet in the literature on the age groups to be considered. Other studies on driver drowsiness describe age groups such as young (18 $\pm$ 24 years), intermediate (24 $\pm$ 45), middle-aged (45 $\pm$ 64), old (65+) [27], or 25–34 years, 35–44 years, 55–64 years, 65 years, and over [26]. Some studies of driver drowsiness only present the average values (e.g., mean age of 36.2 $\pm$ 16.4 years) [28], or the range (e.g., between 26 and 65 years) and mean 37.95 $\pm$ 12.81 years [8]. Studies of age and automation describe age groups in decades [21,22] or considered drivers younger and older than 45 years [23]. Sleep studies describe age groups in decades [44] or five-year age groups. For example, Ohayon et al. [46] performed a meta-analysis of sleep across the human lifespan using data from 65 studies performed with 3577 participants divided in five-year age groups.

6. Conclusions

For several years, the market introduction of conditional vehicle automation according to SAE J3016 level 3 was obstructed due to undefined procedures for vehicle certification. It has been especially difficult to monitor the driver's ability to handle take-over requests when the automation system recognizes inappropriate system functions outside of the operational design domain. Therefore, the UN regulation No. 157 for Automated Lane Keeping Systems has been developed and approved; however, this procedure focuses on monitoring the driver's gaze, without taking into account the driver's actual mental performance in operating an automated vehicle and the related human factors.

The results of this study show that although automation generally has a positive effect to reduce drivers' workload, other factors such as drivers' age and condition also play a significant role. The optimum levels of effort and automation support depend also on drivers' age and condition (fatigued or rested), which modulate the effect of automation. The study also showed that drivers in the automated vehicle mode showed slower reaction times, which would affect take-over procedures. We recommend that the design of future systems needs to compensate for the driver's age, condition, and reaction time for proper human–machine interaction.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/safety8020030/s1, Table S1. Workload self-ratings of female and male drivers from both age groups related to manual and automated driving in the rested and fatigued conditions; Table S2. PERCLOS of female and male drivers from both age groups related to manual and automated driving in the rested and fatigued conditions; Table S3. KSS self-ratings of female and male drivers from both age groups related to the baseline before-test, manual and automated driving in the rested and fatigued conditions; Table S4. Reaction time (RT) of female and male drivers from both age groups related to manual and automated driving in the rested and fatigued conditions; Table S5. Non-parametric Spearman's coefficients of correlation between subjective fatigue, age, and PERCLOS (* Indicates significant correlations at $p < 0.05$).

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