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Fatigue and Secondary Media Impacts in the Automated Vehicle: A Multidimensional State Perspective

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Abstract: Safety researchers increasingly recognize the impacts of task-induced fatigue on vehicle driving behavior. The current study (N = 180) explored the use of a multidimensional fatigue measure, the Driver Fatigue Questionnaire (DFQ), to test the impacts of vehicle automation, secondary media use, and driver personality on fatigue states and performance in a driving simulator. Secondary media included a trivia game and a cellphone conversation. Simulated driving induced large-magnitude fatigue states in participants, including tiredness, confusion, coping through self-comforting, and muscular symptoms. Consistent with previous laboratory and field studies, dispositional fatigue proneness predicted increases in state fatigue during the drive, especially tiredness, irrespective of automation level and secondary media. Similar to previous studies, automation slowed braking response to the emergency event following takeover but did not affect fatigue. Secondary media use relieved subjective fatigue and improved lateral control but did not affect emergency braking. Confusion was, surprisingly, associated with faster braking, and tiredness was associated with impaired control of lateral position of the vehicle. These associations were not moderated by the experimental factors. Overall, data support the use of multidimensional assessments of both fatigue symptoms and information-processing components for evaluating safety impacts of interventions for fatigue.

Keywords: fatigue; driver behavior; driving simulator; automation; media use; alertness; vehicle control

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1. Introduction

Parts of the data reported in this article have previously been published as a conference proceedings paper [1]. This article reports substantial new findings on individual differences in fatigue response and performance. The safety impacts of driver fatigue are substantial and well-known. Cognitive fatigue induced by prolonged driving can lead to impairments in attention and performance during the daytime, beyond impacts of sleep loss and circadian rhythms [2,3]. Professional drivers, including truck and taxi drivers, report prolonged driving time as a major influence on fatigue [4]. Task-induced driver fatigue has been highlighted because of interest in vehicle automation. At SAE Level 3 automation [5], the driver may be required to resume control following an extended period of automated driving. Even short periods of full automation can induce large magnitude increases in fatigue and loss of alertness prior to resuming manual driving [6], raising safety concerns. This article addresses individual differences in susceptibility to fatigue states resulting from automation. We report a study that investigated trait predictors of multiple state fatigue dimensions during automated driving and state correlates of driver performance.

1.1. Individual Differences in Fatigue: Traits and States

Individual differences are expressed in both the driver's stable disposition to become fatigued, and the immediate experience of transient fatigue states. Traits associated with fatigue-proneness interact with situational factors, including drive duration, cognitive workload, and monotony, to produce fatigue states [7]. Research has often used scales for sleepiness to assess fatigue, but it is important to distinguish mental fatigue produced by the task from sleepiness; these two states differ in their causes and in behavioral or symptomatic outcomes [8]. Task-induced state fatigue can be characterized within the multidimensional model of stress that differentiates task engagement, distress, and worry [9]. Both driving simulator and on-road studies show that longer drives tend to elicit lower task engagement and higher distress. Prolonged driving also increases some aspects of worry, including cognitive interference from concerns about task performance [10]. There is an important distinction between active fatigue, associated with cognitive overload, and passive fatigue, associated with boredom when workload is low [11,12]. Both active and passive fatigue are associated with tiredness and task disengagement that escalates over time, whereas active fatigue additionally provokes emotional distress [6].

More fine-grained analyses of fatigue state dimensions have been conducted in occupational and clinical contexts [13,14]. Tiredness is the most salient feature of the state, but fatigued individuals also commonly experience loss of motivation, distraction, concerns about performance, and bodily discomfort [15–17]. Hitchcock and Matthews (2005) [18] differentiated four distinct conceptual aspects of driver fatigue, summarized in Table 1. First, there are core emotional–motivational symptoms including tiredness, task disengagement, and effort-minimization. Second, physical symptoms include muscle fatigue, eyestrain and other somatic disturbances. Third, fatigue may be associated with cognitive disturbances including loss of alertness, distractibility, confused thinking, and metacognitive awareness of impairment. Fourth, drivers attempt to cope with adverse states through a variety of behavioral and self-regulative strategies [19,20]. In the case of fatigue, these strategies include maintaining personal comfort by minimizing task effort and trying to elevate arousal through strategies such as playing music or blasting cold air. Building on an earlier effort [21], Hitchcock and Matthews (2005) [18] developed the Driving Fatigue Scale (DFS) to assess multiple fatigue dimensions within each conceptual category.

Table 1. Four conceptual elements of driver fatigue states.

Conceptual Category	Symptoms	Performance Impact	Safety Implications
Core affective-motivational symptoms	Tiredness, sleepiness, de-motivation	Loss of attentional resources, slowed response, reduced on-task effort	Impaired attention to traffic environment
Physical	Muscle stiffness and discomfort, visual disturbance, headache	Source of distraction	Direct impact of distraction on safety unknown
Cognitive	Mind-wandering, confusion, intrusive thoughts, performance concerns	Cognitive interference associated with loss of working memory and resources	Impaired attention to traffic environment
Coping	Self-arousal, comfort seeking, mental withdrawal	Mixed–depends on strategy	Mixed–depends on strategy

There is an extensive literature on personality trait correlates of fatigue, across multiple contexts. Studies based on the Five Factor Model of personality [22] have found that, overall, neuroticism is associated with higher fatigue, whereas extraversion, conscientiousness, openness, and agreeableness are related to lower fatigue [23]. In task performance contexts, low conscientiousness is the most consistent predictor of acute fatigue states [24]. However, standard personality measures do not adequately capture driving-specific traits that influence the driver's state responses to the challenges of operating a vehicle [25].

The Driver Stress Inventory (DSI) was developed to address this limitation and assess traits specific to the driving context [26]. The DSI assesses five driving trait dimensions associated with dislike of driving, aggression, thrill-seeking, hazard monitoring, and fatigue-proneness. These scales correlate with various safety-relevant stress and performance criteria in both laboratory and field studies [19,27,28]. For example, the fatigue-proneness scale consistently predicts symptoms of state fatigue and task disengagement [10]. Other DSI factors related to vulnerability to negative mood states, including aggression and dislike of driving, also predict elevated fatigue [10,21]. Furthermore, the transactional model of driver stress and fatigue [19] proposes that trait factors influence state fatigue through biasing cognitive stress processes, i.e., appraisal and coping. In general, drivers who use avoidant coping in preference to task-focused coping are more vulnerable to task fatigue. In contrast, appraising the driving task as a stimulating challenge tends to counter development of fatigue states [6]. In this context, trait fatigue-proneness may influence whether the driver's style of appraisal and coping during prolonged driving tends to exacerbate or mitigate fatigue [29].

1.2. Fatigue and Vehicle Automation

Driver fatigue issues have been highlighted in relation to safety in automated vehicles. At higher levels of automation [5], the driver's role changes from active vehicle operation to monitoring vehicle status and maintaining readiness to resume manual control. The task underload and monotony associated with automation monitoring elevates driver passive fatigue and threatens the driver's ability to manage resumption of normal driving [12,30]. Studies of automation impacts show effects on both subjective fatigue [31,32] and performance indices, including loss of vigilance [33,34], slowed secondary task reaction time [31] and delayed manual takeover [35].

The authors' previous studies [36] used a driving simulator to investigate the build-up of subjective fatigue during automated driving, and the impact of automation on speed of response to an emergency event soon after manual takeover. Saxby et al. (2013) [6] compared the effect of full vehicle automation (passive fatigue) with an active fatigue manipulation that exposed the driver to frequent, strong wind gusts. Both active and passive fatigue manipulations lowered task engagement (more strongly for passive fatigue), but only active fatigue elevated distress and workload. Passive but not active fatigue was associated with slowed braking response to the emergency event of a slow-moving van pulling out in front of the driver. Drivers given voluntary control over automation use remained fatigued and were slow to respond to the emergency event, highlighting the adverse safety impact of full vehicle automation [37].

Additional tasks secondary to driving may counter fatigue associated with the underload states that result from monotonous driving. Gershon, Ronen, Oron-Gilad and Shinar (2009) [38] had drivers complete a monotonous 140 min simulated drive during which variability in lane position and speed increased with time on task, suggesting progressive impairment in vehicle control over time. They developed an interactive trivia game that mitigated performance deficits. Aspects of the driving task itself, such as speed regulation, can also be gamified to counteract fatigue [39]. Similarly, two studies [40,41] showed that an additional word-association task enhanced lane-keeping and reduced fatigue effects. A simulated interaction with a virtual digital assistant improved subjective energy and multiple aspects of performance [42]. A subsequent study using this method suggested benefits were greater for drivers more actively engaged with the assistant [43].

Studies of countermeasures designed specifically to counteract automation-induced fatigue are few. A simulator study of automated driving [30] compared the impacts of a quiz game and a monotonous monitoring task on manual takeover, both requiring touchscreen responses to visual stimuli. The more engaging quiz task speeded initial braking response to a crashed vehicle in the driver's lane. The additional task manipulation had no effect on subjective sleepiness. Neubauer, Matthews and Saxby [44] found that both texting and engaging in spoken conversation during the automated phase of a drive were effective in preventing slowed braking to an emergency event following manual takeover. However, engaging in a phone conversation immediately following takeover had no impact on braking speed in the same paradigm [45]. Secondary media use is promising for mitigating automation-induced fatigue, as for fatigue in general, but its impacts appear to vary with modality of stimuli and scheduling of media use across automated and manual phases of driving [36].

1.3. Decomposing Fatigue Processes

A further challenge for understanding fatigue impacts in the automated vehicle is the multiplicity of paths through which fatigue states may impair performance. Much task-induced fatigue research, especially in vigilance paradigms, shows temporal deterioration in attention consistent with an attentional resource model [46] that poses a threat to automated vehicle operation [33,34]. Supporting the resource model, fatigue-related impairments are most prevalent when cognitive workload is high [47]. Psychophysiological studies of fatigue and vigilance using hemodynamic [48] and electroencephalographic (EEG) measures [49,50] show temporal declines in brain activity consistent with the workload/resource model.

However, the role of temporal resource depletion in driver fatigue impairments is uncertain, especially in states of passive fatigue that are associated with low workload. If workload is low, resource availability may be sufficient to maintain performance even if the resource pool becomes depleted. An alternative hypothesis is that the fatigued driver becomes reluctant to exert effort [51]. Fatigue leads to a lowering of performance standards and task strategies that minimize effort, such as responding reactively rather than proactively [16]. Matthews and Desmond (2002) [52] tested resource depletion and effort-minimization hypotheses against one another in a driving simulation study of induced fatigue. Results decisively supported the effort-minimization account of performance deficits, which were seen only in lower workload conditions. Thus, in passive fatigue states, failure to exert sufficient effort may have stronger safety impacts than lack of resources. Other possible mechanisms for fatigue effects include mind-wandering [53] and impairment in visual search [54].

Safety in the automated vehicle may be affected by multiple fatigue processes acting simultaneously. Consistent with this suggestion, studies have shown dissociations between different fatigue responses. Both Atchley et al. (2014) [41] and Neubauer et al. (2012c) [44] found that additional tasks improved performance in the fatigued driver, but they did not mitigate loss of subjective task engagement, a primary state fatigue symptom. Additionally, Saxby et al. (2013) [6] found that passive fatigue, provoked by automation, lengthened reaction time to an emergency event but did not reduce variability of lateral position in the interval immediately prior to the event. That is, quality of vehicle control was not diagnostic of alertness. There is similar ambiguity over the role of individual difference factors. Task engagement may index both resource availability, as demonstrated in vigilance studies [24,47,55], and task-directed effort, as evidenced by less neglect of potential targets in a multi-UAV simulation [56].

1.4. Study Aims

The overall aim of the study was to investigate influences on individual differences in fatigue states in the automated vehicle, and their associations with driving performance. The study used a driving simulator that was configured to contrast driving with full automation and normal driving under manual control [6,44,45]. The current study also added a partial automation condition in which speed was automated to test generalization of results, given evidence for fatigue-related impacts of partial automation [57]. The levels of automation thus corresponded to SAE Levels 0 (manual), 1 (partial: brake/acceleration support), and 3 (full). In addition, two forms of secondary media were manipulated to test the impact of additional tasks on fatigue. One group of participants answered trivia questions at two stages of the drive, similar to [38], while a second group engaged in a cell phone conversation. A third control group had no exposure to secondary media.

In all conditions, vehicle control reverted to manual in the last five minutes of the drive. In this interval, drivers were required to respond to an unexpected hazard, a slow vehicle pulling out in from of them. Multiple factors influence braking speed when the driver takes over control following a period of automated driving including distraction from non-driving tasks, hazard criticality, traffic complexity, and design features of the automation [58–60]. The effects of these factors on braking response time are mediated by multiple physical, visual, and cognitive processes, including gaze redirection, situation evaluation, and action selection and execution [61,62]. The present study aimed to test how automation and secondary media impacted emergency braking speed in a simple, controlled scenario; differentiating component processes was beyond the current scope.

The DSI [26] was used to assess driver traits including fatigue proneness, and the DFQ [18,63] assessed driver fatigue and stress states. This design supported investigation of the following research issues.

1.4.1. Influences on Driver Fatigue States

We tested the impact of the experimental manipulations on multiple fatigue state dimensions, and whether these effects were moderated by individual differences in fatigue proneness. Based on our previous studies (e.g., [6]), we expected that automation would elevate driver fatigue, with full automation having a stronger effect than partial automation. Previous studies show that secondary media can mitigate driver fatigue [31,38] and so we anticipated that both the trivia game and cell phone conversation would reduce subjective fatigue. We expected that the trivia game would have stronger benefits for subjective state, because gamification has been shown to benefit driver engagement [39,64].

1.4.2. Individual Differences in State Fatigue Response

We expected that the DSI fatigue proneness dimension would be associated with a stronger fatigue response across all conditions, as in previous studies (e.g., [10]). At the trait level, fatigue proneness is linked to the tendency to use avoidant coping strategies [26]. Automation-induced fatigue increases avoidance and is associated with reduced task-focused coping [6]. Based on these findings, we hypothesized that fatigue-prone drivers would be especially vulnerable to automation fatigue and, therefore, would show larger benefits from secondary media use that elevates cognitive workload. We tested for differences in DSI predictors of the multiple aspects of fatigue assessed by the DFQ on an exploratory basis.

1.4.3. Automation and Media Influences on Driver Performance

Our previous simulation studies showed that automation-induced fatigue reliably slows braking response to an emergency event occurring soon after manual takeover [6,37]. We tested for replication of this effect and its generalization to partial automation. We also found that the fatigue effect is mitigated by responding to texts during a period of automated driving [44]. Thus, we anticipated that the secondary media, especially the trivia game, would speed response to the emergency event, following manual takeover.

In normal driving, with full manual control, induced driver fatigue impairs lateral control of the vehicle, especially under low workload [52]. We assessed the standard deviation of lateral position (SDLP) during two phases of the first 40 min of the drive in manual and partial automation conditions. We anticipated that secondary media would mitigate fatigue effects and reduce SDLP, similar to previous studies [38,40–42].

1.4.4. Individual Differences in Driver Performance

Subjective fatigue states, including low task engagement, have been linked to both reduced resource availability [55] and reduced task-directed effort [56]. We anticipated that subjective fatigue states would be associated with slowed emergency braking, as well as higher variability in lateral position in manual and partial automation conditions. The diagnosticity of fatigue states for performance impairment may vary with task demands, but it is hard to tease apart the roles of resource availability and effort-regulation. Therefore, we tested, on an exploratory basis, whether fatigue state–performance associations were moderated by secondary media and vehicle automation manipulations.

2. Method

2.1. Participants

Participants were 180 fully licensed drivers (71 males, 109 females) recruited from the University of Cincinnati Introductory Psychology student research pool. The participant pool roughly reflects the ratio of male to female students at the University. Participants ranged in age from 18–30 years (M = 20 years, SD = 3.5). They were required to have normal or corrected-to-normal vision.

2.2. Design

A 3 × 3 (Automation × Secondary media) between-subjects design was utilized. Automation conditions included manual, partial, and total automation. Media conditions included control (no media), trivia, or cell phone conversation. 20 participants were assigned at random to each of the nine task conditions thus defined. The ratio of males to females was similar in each group; a χ^2 test for differences in the frequencies of each gender across conditions was non-significant. In addition, a 3 × 3 (Automation × Secondary media) Analysis of Variance (ANOVA) with DSI fatigue proneness as the dependent variable showed no significant effects of the experimental factors, i.e., participant groups in each condition were equally fatigue-prone.

2.3. Apparatus

2.3.1. Simulator

Drives differing in automation level were configured for a Systems Technology, Inc., STISIM Model 400 simulator, version 2.08.10. The traffic environment was displayed via a 42" Westinghouse LCD flat screen television. The participants were seated in an adjustable car seat and controlled the vehicle via gas and brake pedals and a Logitech MOMO Racing Force Feedback Wheel which provided speed-sensitive "steering feel" feedback via a computer-controlled torque motor (see Figure 1).

2.3.2. Secondary Media

Participants in the cell phone condition were provided with an LG Rumor 2 cellular telephone, together with a JABRA Bluetooth headpiece, which supported hands-free communication with the experimenter.

2.4. Questionnaires

Driver Stress Inventory (DSI: [26]). The first section of the DSI assesses demographic variables, driver experience, accident involvement, and traffic law convictions. The second section comprises 48 questions about the driver's typical emotional reactions, habits, and preferences, answered on 0–10 Likert scales. Responses are scored to compute five dimensions that characterize driver stress vulnerability: aggression, dislike of driving, hazard monitoring, thrill seeking and fatigue proneness. Sample items included "Driving brings out the worst in people" (aggression), "I feel tense and nervous when passing another vehicle" (dislike of driving), "I make a special effort to be alert even on roads I know well" (hazard monitoring), "I like to raise my adrenaline levels while driving" (thrill seeking), and "When driving for several hours, I become more drowsy or sleepy" (fatigue proneness). Scale reliabilities (alpha coefficients) range from 0.73–0.87 [26].

Figure 1. STISIM Model 400 simulator used in study.

Driver Fatigue Questionnaire (DFQ): [18,63]. The DFQ includes 42 items that require the respondent to rate how much they feel various acute fatigue symptoms, answered on 0–5 Likert scales anchored by "not at all" and "very much". It is scored on seven dimensions of fatigue states. Here, to simplify data reporting, we focus on four 6-item scales that are representative of the four conceptual elements of driver fatigue states previously identified. Physical fatigue was represented by muscular fatigue. Sample symptoms are "muscles ache" and "shoulders are stiff". Core fatigue symptoms were represented by tiredness, e.g., "over-tired", "half-awake". Cognitive symptoms were represented by confusion, e.g., "easily distracted", "daydreaming". Coping was represented by comfort-seeking, e.g., "need to rest and relax", "want to take things easy". Alpha coefficients for these scales range from 0.89–0.94.

Participants also completed the Dundee Stress State Questionnaire (DSSQ: [65]) as a general assessment of task stress, but results from the DSSQ are not reported here, in order to focus on the DFQ state fatigue dimensions.

2.5. Procedure

Following an informed consent interview, participants completed the DSI and pre-task versions of the DSSQ and DFQ. Participants were then given instructions for the experimental condition to which they were assigned. They completed a 3-min practice drive in order to familiarize themselves with the simulator. They were instructed to obey all traffic signals and signs, including speed limit signs, stop signs, and red lights. Participants in the cell phone condition received a practice call at approximately 1:30 min to confirm their ability to use the Bluetooth device.

Participants next completed a 45 min drive on a two-lane highway, with occasional oncoming traffic, pedestrian crossings, and intersection stops. The scenery was varied throughout the drive and transitioned between rural (small town) and city (urban) scenery approximately every 5 min, similar to previous studies [6,37,44]. In the manual driving condition, participants were asked to keep to speed limits shown on signs. Speed limits ranged from 40–50 mph in rural environments, and 50–60 mph in city driving.

The timeline of the drive is shown in Figure 2. During the first 40 min, the participant's level of control of the vehicle was set at the beginning of the drive according to automation condition. In manual conditions, participants used the wheel and pedals as in normal driving. In partial automation conditions, speed was controlled by the simulation, and the participant steered the vehicle. Under full automation, both speed and steering were controlled by the simulation. In both automation conditions, participants were instructed to monitor for an automation failure, in order to keep their attention on the display. Automation function was indicated by two red diamonds positioned at the upper left- and righthand corners of the screen. Approximately every 10 min, one of the red diamonds was replaced by a downward pointing triangle indicating "automation failure". In this event, participants were instructed to press the turn signal when they detected the failure in order to reset the automation. There was, in fact, no interruption of automation until the automation was switched off at 40 min, requiring the participant to take over full vehicle control.

Figure 2. Timeline for simulated drive, by experimental condition.

The secondary media manipulation was implemented as follows. Secondary media were delivered during two 10-min periods (between 5–15 min and 30–40 min during the drive). In the trivia condition, the experimenter sat out of view of the participant and communicated by speech, in a neutral tone. Based on Gershon et al.'s (2009) [38] procedure, participants first selected one of five categories-food, movies, sports, current events, and general knowledge and informed the experimenter of their choice. The experimenter then referred to a list of questions for that category and asked the participant the next question on the list. Following the participant's spoken answer, the experimenter stated "correct" or "incorrect". The trivia game was performed during two separate 10-min periods, as shown in Figure 1. In the cell phone condition, the experimenter conducted two conversations by phone during these 10-min intervals. Conversations consisted of a general introduction followed by the recollection of a more in depth "close call" experience of the participant, following Saxby et al.'s (2017) [45] methodology. The close call method is considered engaging to the participant and representative of a naturalistic conversation [66]. In the control condition, there was no communication between experimenter and participant. Standard deviation of lateral position (SDLP) was logged during mins 8–12 and 33–37, providing measures of control early and late in the drive, concurrent with secondary tasks where provided.

In the final 5 min of the drive (i.e., 40–45 min), all participants reverted to full manual control, with no secondary media. After 42 min, an emergency event was triggered by the experimenter. A van suddenly appeared at the side of the road and followed the same scripted trajectory for all participants. After 3 s the van pulled out in front of the driver at slow speed (see Figure 3), requiring the participant to brake or swerve to avoid collision. Braking response time (RT) was logged, as well as whether the participant actually collided with the van. The van pulled back on to the right shoulder 30 s after the event was triggered.

Following termination of the drive, participants completed post-task versions of the DFQ and DSSQ, followed by debriefing.

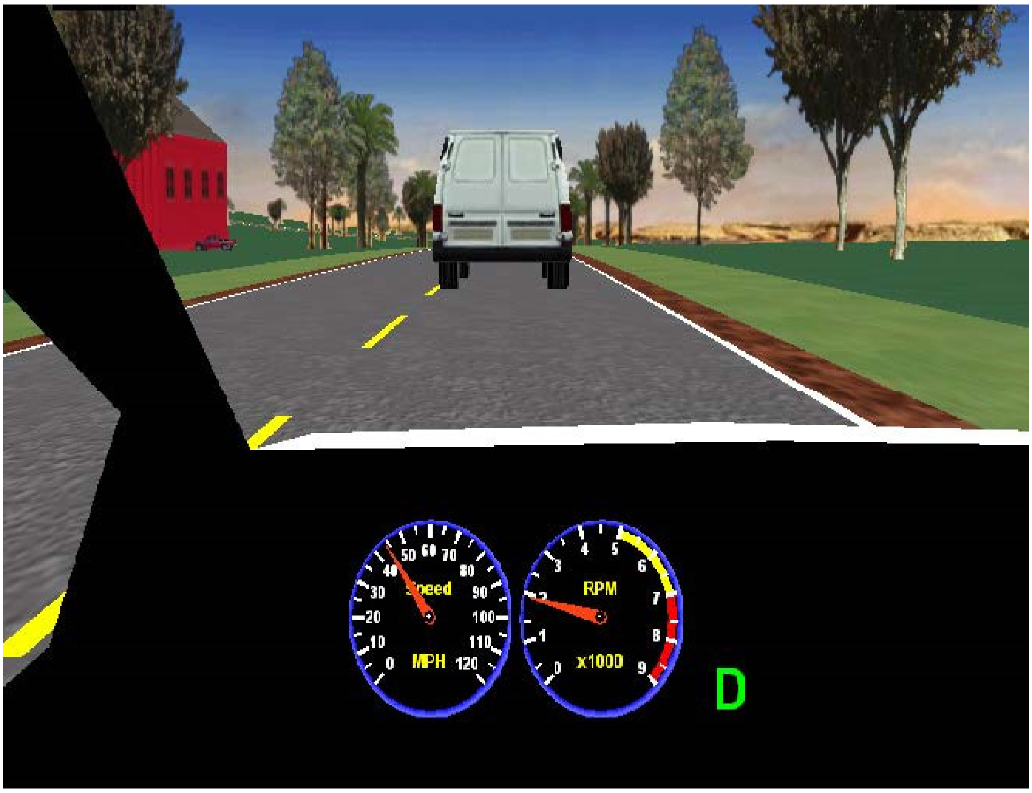

Figure 3. Screenshot of van pulling out in front of driver.

3. Results

3.1. Overview of Data Analysis

Data were analyzed as follows. First, we ran mixed-model ANOVAs to test the effects of the automation and secondary media on fatigue states, assessed by the DFQ. These analyses confirmed that the drive was generally fatiguing and identified impacts of automation and media on specific dimensions of fatigue. Second, we conducted correlational and regression analyses to investigate relationships between predisposition to driver stress and fatigue, assessed by the DSI, and DFQ fatigue states. These analyses showed multiple associations between DSI and DFQ dimensions, confirming that the DSI predicts fatigue state change during driving. However, these associations were not further moderated by the experimental factors. Third, we ran ANOVAs to test the effects of automation and secondary media on driving performance. ANOVAs confirmed that automation slowed braking RT to the emergency event, whereas secondary media enhanced vehicle control in the first parts of the drive but did not affect emergency braking. Finally, we conducted correlational and regression analyses on relationships between DFQ dimensions and performance metrics. The majority of fatigue state dimensions were associated with poorer vehicle control; surprisingly, higher DFQ confusion correlated with faster emergency braking.

3.2. Effects of Automation and Secondary Media on Fatigue States

Four 2 × 3 × 3 (pre/post × automation × secondary media) mixed-model ANOVAs were run to test the effects of experimental factors on the four DFQ state fatigue dimensions. Pre/post was a repeated-measures factor contrasting pre- and post-drive DFQ scores. One participant failed to complete the post-drive DFQ, and their data were omitted from these analyses. Main effects of pre/post were significant for muscular fatigue (F(1,170) = 45.53, $p < 0.01$, $\eta^2_p = 0.211$), tiredness (F(1,170) = 91.08, $p < 0.01$, $\eta^2_p = 0.349$), confusion ($F(1,170) = 34.22$, $p < 0.01$, $\eta^2_p = 0.168$), and comfort-seeking ($F(1,170) = 41.89$, $p < 0.01$, $\eta^2_p = 0.198$). Fatigue state responses can be expressed as change scores from pre- to post-drive, standardized against the SD of the pre-drive state, as shown in Table 2. Distributions of scores were similar to those observed in previous studies using the DFQ [18,63]. Fatigue scores tended to increase on all dimensions during the drive, with the largest effect on tiredness (standardized change score $\Delta_z = 1.13$) and smaller changes in muscular fatigue ($\Delta_z = 0.48$), confusion ($\Delta_z = 0.49$), and comfort-seeking ($\Delta_z = 0.40$). Variation in fatigue response with experimental factors is indicated by a factor × pre/post interaction, i.e., the change in fatigue during the drive varies across experimental conditions. The pre-post × automation interaction was significant for muscular fatigue ($F(2,170) = 4.131$, $p < 0.05$, $\eta^2_p = 0.046$) and the pre/post × media interaction was significant for tiredness ($F(2,170) = 6.26$, $p < 0.01$, $\eta^2_p = 0.069$). There were no other significant interactions.

Table 2. Means (and SDs) of standardized fatigue state changes as a function of automation and secondary media conditions.

Condition	Fatigue State Dimension			
	Muscular	Tiredness	Confusion	Comfort-Seeking
Manual				
Control	0.532 (0.77)	1.793 (1.79)	0.846 (1.396)	0.597 (0.966)
Trivia	0.862 (1.036)	1.217 (1.605)	0.491 (0.837)	0.49 (0.524)
Cellphone	0.567 (0.933)	0.825 (1.375)	0.26 (0.837)	0.149 (1.088)
Partial Auto				
Control	0.532 (1.132)	2.134 (2.27)	0.888 (1.45)	0.49 (0.987)
Trivia	0.549 (0.963)	0.681 (1.663)	0.019 (1.022)	0.44 (0.827)
Cellphone	0.718 (0.941)	0.707 (1.263)	0.369 (1.1)	0.355 (0.54)
Full Auto				
Control	−0.243 (1.226)	1.217 (1.159)	0.388 (1.014)	0.263 (0.929)
Trivia	0.439 (0.775)	0.932 (1.634)	0.846 (1.353)	0.628 (0.729)
Cellphone	0.382 (0.685)	0.694 (1.232)	0.303 (0.872)	0.206 (0.684)

Note. Standardized change scores calculated as (post-task state–pre-task state)/(SD of pre-task state), Auto = Automation.

Figure 4 graphs the two significant interactions. The upper panel shows that manual and partial-automation drives elicited greater muscular fatigue than full automation, which appears to have provided relief from steering the vehicle. Automation did not influence other aspects of fatigue. The lower panel shows that both forms of secondary media reduced the tiredness response but did not mitigate the other fatigue dimensions.

3.3. Predictors of Fatigue States

Table 3 shows pre- and post-drive correlations between DFQ state fatigue dimensions and the DSI scales, representing predispositions to different forms of stress. The 'Change' rows are partial correlations between post-drive fatigue states and DSI scales, controlling for the relevant pre-drive state. A positive partial indicates that the DSI scale predicts an increase in state beyond that expected from the pre-drive level. Three of the DSI scales—fatigue proneness, aggression, and dislike of driving—correlated positively with multiple dimensions of state fatigue, although muscular fatigue was only weakly predicted, with all rs < 0.2. Fatigue proneness and aggression both predicted changes in fatigue state dimensions also, although only fatigue proneness predicted change in comfort-seeking. Dislike of driving was associated with higher levels of fatigue on three of the DFQ scales, but it did not predict change in fatigue state. That is, it appears that high Dislike drivers were fatigued initially, and their fatigue persisted through the drive without increasing disproportionately.

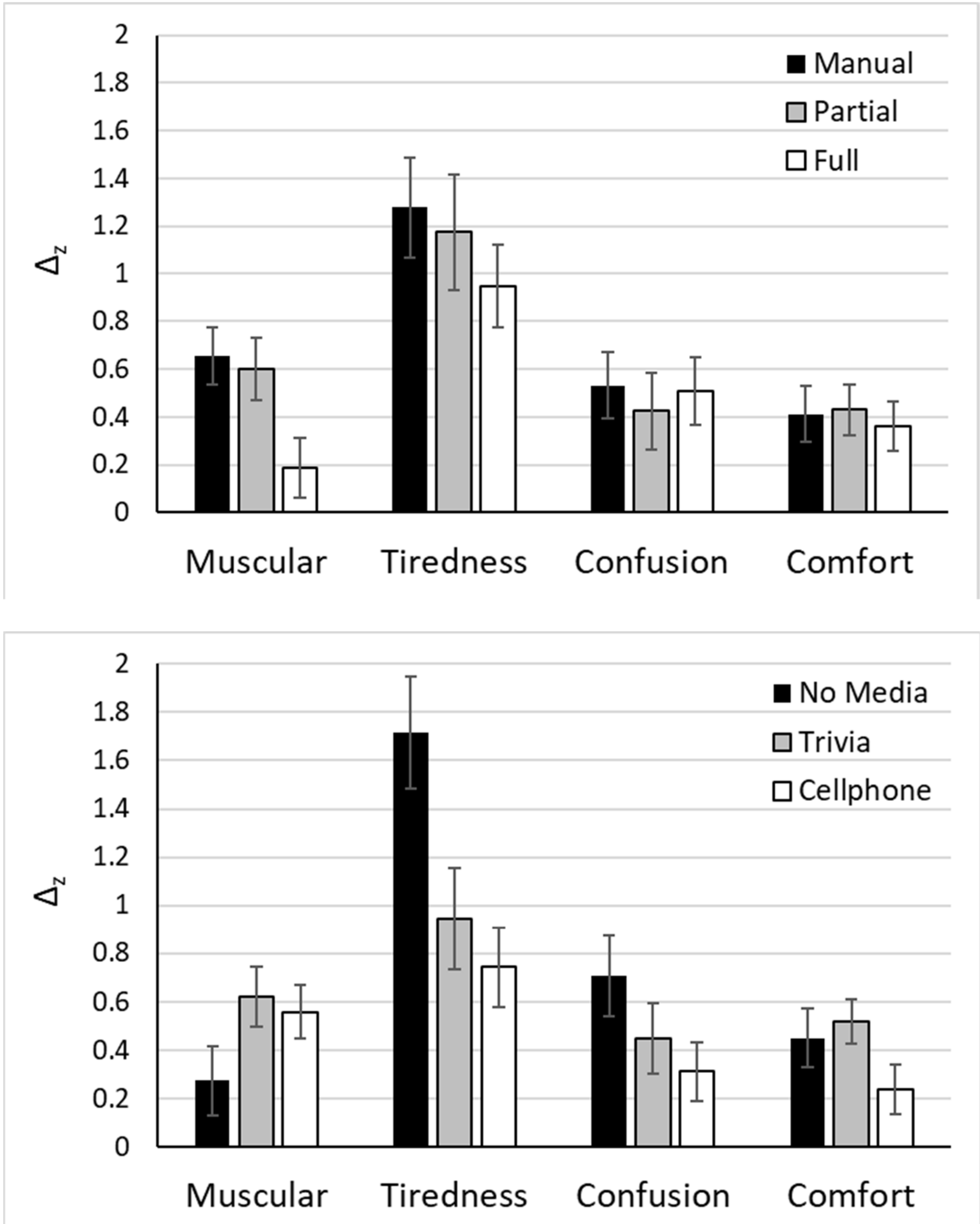

Figure 4. Mean standardized change scores on four state fatigue dimensions as a function of (1) automation condition (**upper panel**) and (2) secondary media condition (**lower panel**). Error bars are standard errors.

We ran multiple regressions to test whether associations between the DSI and fatigue states remained significant with experimental factors controlled. The regressions included automation and secondary media factors as categorical predictors. The three levels of each experimental factor were represented with two effect coded variables for each factor [67]. With each post-drive fatigue state as the dependent variable, successive steps entered (1) the corresponding pre-drive state, (2) the two automation variables, (3) the two secondary media variables, and (4) the five DSI variables. There was no evidence of automation × media interactions in the ANOVAs, so no interaction terms were included. Table 4 provides summary statistics. Pre-task state made a substantial contribution to each equation, reflecting correlations between pre-drive and post-drive scores. Consistent with the ANOVAs, automation influenced muscular fatigue and secondary media influenced tiredness. As a block, the DSI variables added significantly only to the prediction of tiredness. In the final equation, fatigue proneness ($\beta = 0.140$, $p < 0.05$) and aggression ($\beta = 0.158$, $p < 0.01$) both made significant contributions. In the equation for confusion, the joint contribution of the DSI variables at step 4 just failed to reach significance (p = 0.054) and hazard monitoring was significantly negatively associated with confusion in the final equation ($\beta = -0.139$, $p < 0.05$). In these, and all subsequent regressions, collinearity statistics were within acceptable levels.

Table 3. Correlations between DSI scales and four fatigue state dimensions.

Fatigue State		DSI Scale				
		Fatigue Proneness	Aggression	Dislike of Driving	Hazard Monitoring	Thrill Seeking
Muscular	Pre	0.082	0.091	0.040	0.118	0.092
	Post	0.183 *	0.179 *	0.101	0.018	0.085
	Change	0.189 *	0.171 *	0.111	−0.089	0.036
Tiredness	Pre	0.063	0.100	0.215 **	0.124	−0.001
	Post	0.250 **	0.259 **	0.226 **	− 0.015	0.038
	Change	0.268 **	0.252 **	0.117	−0.118	0.050
Confusion	Pre	0.160 *	0.157 *	0.266 **	0.020	0.140
	Post	0.225 **	0.160 *	0.232 **	− 0.132	0.100
	Change	0.178 *	0.084	0.097	−0.177	0.015
Comfort	Pre	0.237 **	0.205 **	0.338 **	0.129	−0.068
	Post	0.279 **	0.225 **	0.270 **	0.048	− 0.056
	Change	0.170 *	0.119	0.053	−0.058	−0.021

Note. Pre = pre-drive. Post = post-drive. Change = partial correlation with post-drive state, controlling for pre-drive state. * $p < 0.05$, ** $p < 0.01$.

Table 4. Summary statistics for regressions of four fatigue state dimensions on pre-task state, experimental factors and DSI scales.

		Fatigue State Dimension							
		Muscular		Tiredness		Confusion		Comfort-Seeking	
Step	*df*	R	ΔR^2	R	ΔR^2	R	ΔR^2	R	ΔR^2
1. Pre-drive state	1177	0.636 **	0.405 **	0.614 **	0.377 **	0.603 **	0.363	0.692 **	0.478 **
2. Automation	2175	0.659 **	0.029 *	0.617 **	0.004	0.604 **	0.002	0.693 **	0.002
3. Secondary media	2173	0.667 **	0.011	0.650 **	0.042 **	0.617 **	0.016	0.708 **	0.021 *
4. DSI scales	5168	0.684 **	0.022	0.708 **	0.078 **	0.648 **	0.039	0.720 **	0.018

Note. * $p < 0.05$, ** $p < 0.01$. R = multiple correlation coefficient; ΔR^2 = step change in R^2

We ran further regressions to test whether relationships between fatigue proneness and fatigue state were moderated by experimental condition. Moderator effects would indicate that the capacity of fatigue proneness to predict fatigue states varied with levels of automation and/or secondary media delivery. Fatigue proneness × automation and fatigue proneness × secondary media interaction terms were computed by centering fatigue proneness and calculating its products with the effect coded variables for the experimental factors, i.e., four product terms in total. We repeated the regressions, first, adding fatigue proneness × automation terms at step 5, and second, adding fatigue proneness × media interaction terms at step 5. For the interactions with automation, the final step added from 0.001–0.008 to R^2 and the increments to R^2 were non-significant in all four equations. For the media interaction terms, all contributions of the interactions were also non-significant, with the increments to R^2 varying from 0.002–0.009. Thus, there was no evidence that associations between fatigue proneness and fatigue states were moderated by either level of automation or provision of secondary media.

3.4. Effects of Automation and secondary Media on Performance

Braking RT was log-transformed prior to analysis to correct positive skew. The analysis of RT was based on 154 participants as 26 failed to brake. Across the three automation conditions, frequencies of failing to brake were 3/60 (manual), 10/60 (partial automation) and 13/60 (full automation). The difference between automation conditions was significant ($\chi^2(2) = 7.10$, $p < 0.05$). That is, both types of automation reduced probability of braking. Frequencies of braking were similar across the three secondary media conditions. 118 drivers actually crashed into the van, but frequencies were similar across the different automation and media conditions.

The effects of the experimental factors on braking RT were analyzed with a 3 × 3 (automation × secondary media) between-groups ANOVA. The main effect of automation was significant ($F(2,145) = 6.24$, $p < 0.01$, $\eta^2{}_p = 0.079$) but there was no main or interactive effect of media. Table 5 shows the cell means for the analysis and Figure 5 illustrates the automation effect. Braking RT was faster with manual control than with either form of automation.

Table 5. Log RTs (and SDs) for braking response as a function of secondary media and automation conditions.

Automation	Secondary Media		
	None	**Trivia**	**Phone**
Manual	0.408 (0.266)	0.450 (0.266)	0.459 (0.223)
Partial Auto	0.583 (0.257)	0.709 (0.418)	0.553 (0.350)
Full Auto	0.667 (0.250)	0.651 (0.339)	0.617 (0.486)

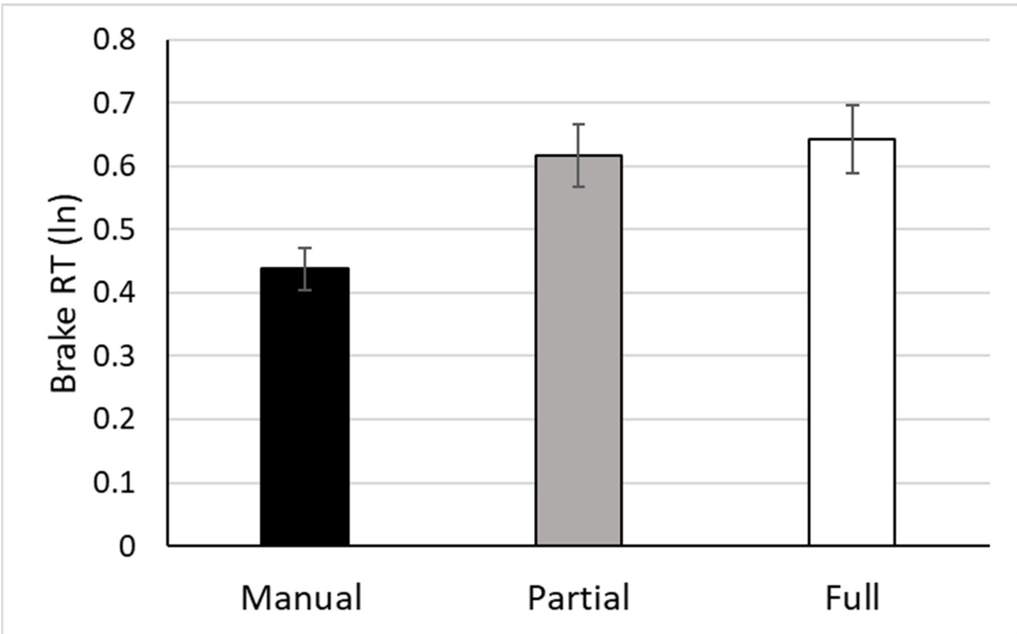

Figure 5. Mean braking RT in three automation conditions, averaged across secondary media conditions. Error bars are standard errors.

Effects on SDLP early (8–12 min) and late (33–37 min) in the drive were analyzed for drivers in the manual and partial automation conditions. SDLP was log-transformed to reduce positive skew. A 2 × 2 × 3 (early/late × automation × secondary media) mixed-model ANOVA showed several significant effects on SDLP. There were significant main effects of early/late ($F(1,114) = 81.63$, $p < 0.01$, $\eta^2{}_p = 0.417$) and secondary media ($F(2,114)=14.16$, $p < 0.01$, $\eta^2{}_p = 0.199$). SDLP declined over time, suggesting a practice effect.

SDLP was lower in both secondary media conditions relative to no media. These effects were modified by two significant interactions: early/late × automation (F(1,114) = 10.22, $p < 0.01$, $\eta^2{}_p = 0.199$), and automation × media (F(2,114) = 3.11, $p < 0.05$, $\eta^2{}_p = 0.052$). Figure 6 shows the cell means. Early in the drive, SDLP tended to be lower with partial automation than with manual control, but the automation effect diminished later in the drive. The apparent practice effect may have been accelerated in the partial automation condition given that the driver could focus attention on lateral control. The automation × media interaction reflects greater benefits of media under partial automation.

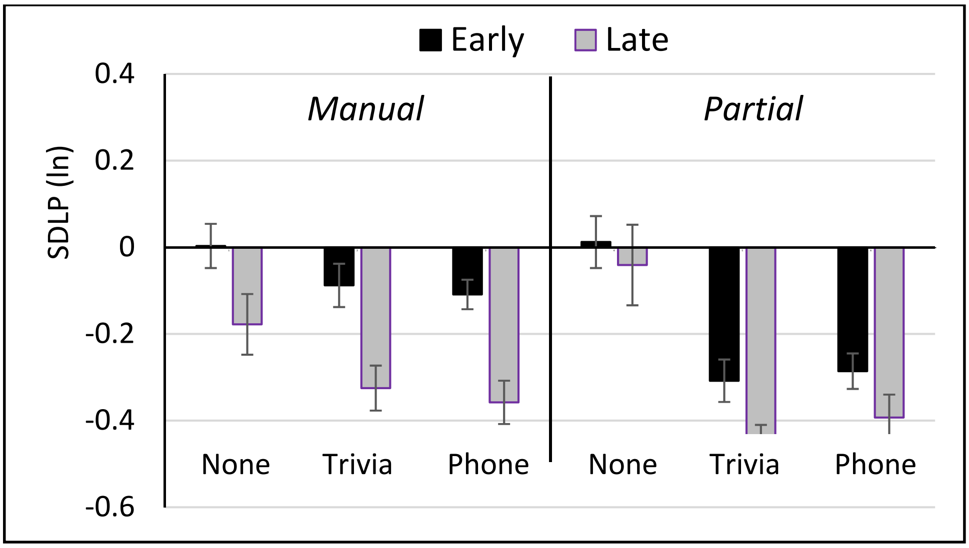

Figure 6. SDLP as a function of automation and secondary media conditions, early and late in the drive. Error bars are standard errors.

3.5. Performance Correlates of Fatigue States

Correlations between post-drive DFQ scores and SDLP early and late in the drive and braking RT (performance variables log-transformed) are shown in Table 6. Data for SDLP were taken from the partial automation and manual conditions (N = 120). Table 6 shows that only confusion correlated with braking RT; surprisingly, more confused drivers were *faster* to brake. Table 7 shows the multiple regression that controlled for the effects of the experimental manipulations. The four DFS scales made a significant contribution to the equation at the final step and the only significant DFS predictor in the final equation was confusion ($\beta = -0.232$, $p < 0.05$). Additional regressions tested for interaction between confusion and the experimental factors, but no significant effects of interaction terms were found.

Table 6. Correlations between four fatigue state dimensions and performance measures.

	Fatigue State Dimension			
	Muscular	**Tiredness**	**Confusion**	**Comfort-Seeking**
SDLP (1st half)	0.060	0.366 **	0.327 **	0.188 *
SDLP (2nd half)	0.067	0.363 **	0.236 **	0.194 *
Braking RT	−0.156	−0.154	−0.256 **	−0.034

Note. * $p < 0.05$, ** $p < 0.01$.

Table 7. Summary statistics for regression of braking RT on experimental factors and DFQ scales.

Step	*df*	Braking RT	
		R	ΔR^2
1. Automation	2176	0.258 **	0.067 **
2. Secondary media	2174	0.265 *	0.004
3. DFQ scales	4170	0.349 **	0.052 *

Note. * $p < 0.05$, ** $p < 0.01$. R = multiple correlation coefficient; ΔR^2 = step change in R^2.

Table 6 shows that all fatigue states except muscular fatigue were significantly correlated with higher SDLP, at both stages of the drive. We ran multiple regressions for each SDLP measure, with four steps. We entered successively (1) the automation effect coded variable contrasting manual and partial automation conditions, (2) the two secondary media effect coded variables, (3) automation × media interaction terms, and (4) the four DFQ variables. Interaction terms were included because there was a significant interaction in the ANOVA previously reported. Table 8 gives summary statistics for the two regressions. Consistent with the ANOVA, both regressions showed a significant impact of media on SDLP. The contribution of the DFS scales at step 4 was significant in both instances. DFS tiredness was the only scale that was independently predictive, both for early SDLP ($\beta = 0.334$, $p < 0.01$) and for late SDLP ($\beta = 0.372$, $p < 0.01$). We also tested for interactive effects of tiredness and the experimental factors using the approach described in Section 3.2. Product terms for tiredness × automation and tiredness × secondary media did not add significantly to R^2.

Table 8. Summary statistics for regressions of SDLP early and late on experimental factors and DFQ scales.

Step	*df*	SDLP–Early		SDLP–Late	
		R	ΔR^2	R	ΔR^2
1. Automation	1118	0.263 **	0.069 **	0.020	0.000
2. Secondary media	2116	0.474 **	0.156 **	0.415 **	0.172 **
3. Automation × Media	2114	0.515 **	0.041 *	0.454 **	0.033
4. DFQ scales	5110	0.598 **	0.092 **	0.541 **	0.086 *

Note. * $p < 0.05$, ** $p < 0.01$. R = multiple correlation coefficient; ΔR^2 = step change in R^2.

4. Discussion

The present study investigated relationships between subjective fatigue dimensions, personality, and driving performance in simulated drives that varied in level of automation and provision of secondary media. As expected, we found substantial increases in fatigue during driving, partially mitigated by secondary media. Both full and partial automation slowed emergency braking following manual takeover as in our previous studies [36]. We also replicated previous findings that DSI fatigue proneness predicts increases in state fatigue induced by driving [10]. We found relationships between state fatigue and impaired vehicle control, although the confusion state dimension was unexpectedly associated with faster emergency response. However, we also found various dissociations that support the need for a multidimensional conception of driver fatigue states. In this discussion, we consider further the impacts of the experimental factors on subjective and performance outcomes, followed by an evaluation of findings on individual differences and their safety implications.

4.1. Automation, Secondary Media, and Safety

The automation and secondary media manipulations both influenced fatigue outcomes, but in different ways, implying that they may influence different fatigue processes.

Automation did not influence most aspects of state fatigue. Here, full automation reduced muscular fatigue, presumably reflecting the physical demands of manual vehicle steering. Saxby et al. (2013) [6] found that automation affects fatigue dynamics, in that fatigue develops faster in the automated vehicle than with manual control, but plateaus at a similar level. The current data are consistent with this finding; 45 min is a long enough simulated drive for substantial fatigue to develop during manual driving. Results also show that simulated driving produces especially large increases in tiredness, relative to other aspects of fatigue states. As in multiple previous studies [36], automation slowed response to an emergency event taking place shortly after manual takeover. The current study extended previous findings by showing that even partial automation—similar to driving with cruise control—is sufficient to produce the slowing effect. Typically, it takes drivers 2–5 s to transition safely from automated to manual driving [60]. Here, we observed automation-induced impairment 2 min after the initiation of the takeover, demonstrating a fatigue effect that persisted beyond the automation-to-manual transition. Various authors [68,69] have drawn attention to the safety threats of transitioning from automatic to manual driving at SAE level 3, and the current data reinforce these concerns. They also show that level of subjective fatigue is not necessarily diagnostic of loss of alertness in the takeover scenario.

Based on previous findings [38,41,43], we anticipated that secondary media would mitigate state fatigue, including adverse impacts of automation. This hypothesis was partially supported. Benefits of secondary media included reduced tiredness and improved lateral control of the vehicle, especially as the drive progressed. However, secondary media had no effect on muscular fatigue, confusion, or comfort-seeking, implying that its benefits are selective. In addition, and contrasting with previous findings [44], there was no impact on emergency braking, implying that media use benefits on alertness are fragile and dependent on how additional cognitive workload is delivered. We also found only limited interaction between media and automation. Secondary media did not counteract slowing of emergency braking induced by automation. There was a significant interaction between the two experimental factors in the analysis of SDLP. The benefits of media for lateral control appeared earlier in the drive with partial automation than with full automation. Matthews and Desmond (2002) [52] interpreted fatigue effects on lateral control as reflecting loss of directed-effort, consistent with Hockey's (2012) [16] account of fatigue. The secondary media here appear to have maintained engagement with the task, supporting performance improvement over time. Thus, secondary media use has selective safety benefits. Specifically, the additional workload appears to mitigate loss of task-directed effort under fatigue, but not loss of alertness.

4.2. Individual Differences in Driver Fatigue States

The present study investigated individual differences in both driver fatigue states and performance impairments. Three DSI trait fatigue dimensions—fatigue proneness, aggression, and dislike of driving—were correlated with fatigue states, consistent with previous findings [10,19]. As expected, fatigue proneness was associated with increases during the drive of all four DFQ fatigue dimensions, especially tiredness. More surprisingly, aggression was also associated with increasing tiredness, and, to a lesser degree, with muscular fatigue. Previously, Matthews and Desmond (1998) [21] found significant associations between driver aggression and aspects of driver fatigue during simulated drives designed to be fatiguing. Prolonged driving under relatively low workload conditions may be especially frustrating for drivers prone to aggression. Sleep loss has also been linked to aggression and irritability in multiple studies, suggesting overlap in underlying biological mechanisms [70], although causal effects of prolonged anger on fatigue have not been tested.

Dislike of driving was associated with tiredness pre- and post-drive but not change in tiredness. This association may reflect a general association between dislike of driving and negative moods in the driving context; dislike relates to task-induced state change mainly in overtly threatening driving conditions [19]. Multiple regression analyses provided a slightly different picture of the role of DSI factors. Independent influences of fatigue proneness and aggression on change in tiredness were confirmed. There was also a significant relationship between DSI hazard monitoring and lower confusion, which was not evident in the bivariate correlations.

Overall, data confirm the utility of the DSI for predicting driver fatigue. DSI–fatigue correlations were not significantly moderated by the experimental factors; associations generalized across different levels of automation and secondary media. Thus, the DSI does not predict individuals uniquely sensitive to automation-induced fatigue or media impacts on state.

4.3. Fatigue and Individual Differences in Performance

Results showed that different elements of the fatigue state correlated with the two principal performance outcomes. Tiredness, confusion, and comfort seeking were all associated with poorer lateral control in manual and partially automated driving; the multiple regression suggested that the fatigue effects were attributable primarily to tiredness. Tiredness overlaps substantially with low task engagement, which is associated with both lower resource availability and lower task-directed effort in performance studies [24], as well as poorer lateral control in simulated driving [71]. As task demands in the present study were relatively low, tiredness may be indexing reduced effort applied to vehicle control. Only confusion was associated with braking speed, and, surprisingly, more confused drivers were faster to brake. A tentative explanation is that confused participants responded impulsively without having full situation awareness of their surroundings, whereas those lower in confusion took a little longer to evaluate the situation before responding. Consistent with this suggestion, some research on manual takeover suggests that fatigued drivers may compensate for loss of situation awareness by rapid braking [72,73]. Fatigue also leads to loss of control over initiation of well-learnt motor responses [74], a process that may generalize to emergency braking.

4.4. Practical Implications

The identification of drivers vulnerable to fatigue is important for safety [27,29] but the role of dispositional fatigue-proneness has been neglected. A recent review of personality factors and unsafe driving [75] located multiple factors associated with negative emotions, such as anger and anxiety, but cited no studies of fatigue-prone personality. The current data support the use of the DSI [26] to identify drivers who will show rapid onset of fatigue symptoms during driving. Such individuals may not be well-suited to commercial driving jobs. Assessment of fatigue vulnerability is a useful tool for exploring the safety impacts of clinical disorders and neurological conditions associated with fatigue [27]. However, the DSI was found to be more effective in predicting changes in tiredness than in other dimensions of state fatigue.

Another practical issue is diagnostic monitoring for types and levels of fatigue that threaten safety. In applied settings, objective measures that can be tracked continuously such as eye closures are required [8]. However, subjective state research contributes to differentiating cognitive fatigue processes that can be targeted for monitoring. The current study links impairments in vehicle control to tiredness and impulsive response to emergency events to confusion. This dissociation suggests that behavioral indices of fatigue should be evaluated across multiple cognitive processes vulnerable to fatigue. For example, indices based on analysis of steering movements [76] might not be diagnostic of impulsive response or alertness. The study also suggests that caution should be used in interpreting faster response times as indicative of greater alertness, at the individual driver level, given a possible link to impulsivity.

4.5. Limitations

The study has the normal limitations of laboratory, simulation-based research, i.e., extent of generalization to real-world driving is uncertain. In particular, larger magnitude declines in subjective fatigue are seen in simulator studies than in real-world driving [77]. However, fatigue effects on real-world performance metrics such as those utilized here have been demonstrated, including manual takeover from automation [73]. The value of simulation research is in identifying individual differences in fatigue processes whose impacts can be followed up in real-world contexts [27,29,78]. Further research might discriminate the various physical, visual, and cognitive processes that control emergency braking speeds and their sensitivities to fatigue states [61].

In addition, participants were predominantly young American adults, and generalization to other demographic groups is unknown. It would also have been desirable to include objective, psychophysiological fatigue metrics to complement the subjective state measures, although our previous work suggests that subjective measures have diagnostic validity over and above psychophysiological indices [79]. Finally, the automated driving scenario was rather artificial; drivers in real-life would typically have greater familiarity with the automated systems of their vehicles.

5. Conclusions

Vehicle automation can increase driver vulnerability to task-induced fatigue states and performance impairment. Use of in-car media such as trivia games and phone conversations are promising for mitigating fatigue during automated phases of driving, but the current findings suggest that further work is necessary to develop interventions that can reliably enhance both neurocognitive state and driver performance. We have shown that driver personality is associated with individual differences in state fatigue response that are robust across different levels of automation and provision of secondary media, presenting a challenge to mitigation efforts. Findings also show the utility of the multidimensional perspective on fatigue states for understanding the inter-relationships of personality, state response, and performance impairments. Different aspects of fatigue may be associated with different impairments in information-processing, supporting the need for multidimensional assessments in evaluating the impacts of interventions for driver fatigue.

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