Sound Strategies for Safe Driving: Exploring Auditory Interventions to Counteract Passive Driver Fatigue

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ABSTRACT

Cognitive underload may lead to passive driver fatigue in long, repetitive driving scenarios. While secondary tasks facilitated by in-car voice assistants can act as stimulants, they may distract drivers if not properly designed. Our study examined a range of auditory interventions, e.g., listening to Music or Interactive Story Games, intended to boost driver arousal without compromising driving capabilities. Using EEG and EDA to measure physiological responses and driving performance metrics, we assessed the effectiveness of these auditory tasks. The study also examined the impact of varying levels of driver participation (vocal, physical, or passive) with these interventions. Results showed music significantly boosts arousal with minimal impact on driving ability. Additionally, we found that vocal participation yields a more favourable balance between arousal and deterioration in driving performance compared to passive listening or physical participation. Finally, we discuss how these insights could enhance in-car voice assistants to alleviate passive driver fatigue.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Empirical studies in HCI**.

KEYWORDS

passive driving fatigue, fatigue countermeasure, arousal, voice assistants

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1 INTRODUCTION

In the world of automotive technology, in-car voice assistants are emerging as essential tools for enhancing the driving experience through hands-free operation. They offer convenience and entertainment and play a crucial role in promoting driver well-being by addressing driver fatigue, a significant factor impairing driving abilities. Driver fatigue stems from various sources, including sleep deprivation, cognitive overload (active fatigue), and underload (passive fatigue), with the latter often resulting from prolonged, monotonous driving tasks [5, 12, 14, 18]. Research into detecting driver fatigue has made headway, using sensors to monitor both driver and vehicle behaviours [7, 28, 31, 32]. However, effective interventions, particularly against passive fatigue, are less prevalent (e.g., [1, 18, 19]). Engaging drivers in secondary tasks, like listening to music or conversing, has been shown to boost alertness [1, 4, 13, 33], yet overstimulation could compromise safety. Integrating voice assistants with fatigue detection for tailored auditory interventions might offer a solution to passive fatigue without reducing driving performance.

This study examines the impact of music and interactive stories delivered through in-car voice assistants on driver arousal and performance, focusing on combating passive driving fatigue. Given that such auditory interventions are particularly suited for addressing passive fatigue, we explore their effectiveness on arousal over time [30, 35]. We investigate how different modes of engagement (i.e., passive, vocal, and physical) impact arousal. Our results indicate that music enhanced arousal with a smaller adverse effect on driving performance than interactive stories. We show, that vocal participation was notably more beneficial for maintaining a better arousal to driving performance ratio. Our findings suggest that in-car voice assistants can mitigate passive driving fatigue by suggesting customised activities to prevent monotony and enhance alertness. This research is a step towards leveraging in-car voice assistants to deliver auditory interventions as strategies against passive driving fatigue. This is crucial for maintaining alertness in both manual and semi-automated driving contexts, where driver readiness for takeover remains a paramount safety concern [2, 23]. This approach underlines the ongoing importance of driver engagement and response readiness as vehicle automation advances.

2 RELATED WORK

This section will present the latest research on cognitive stimulation strategies to reduce passive driving fatigue, focusing on the role of voice assistants.

2.1 Cognitive Stimulation to Counter Driver Fatigue

Many cars today are already equipped with in-vehicle warning systems that use auditory alerts to create awareness about driver fatigue [36]. The shortcomings of those alerts are that the effect may be short-lived [35]. A more promising approach to reduce passive fatigue is engagement with secondary tasks as cognitive stimuli [8, 20, 29, 31].

2.1.1 Cognitive stimulation content. Games are a promising cognitively stimulating task used to counter driving fatigue. Neubauer et al. [20] compared the fatigue-countering effect of cell phone conversations and trivia games. They found that those tasks showed seemingly equal effectiveness in countering fatigue. These findings support the effectiveness of cognitive stimulation to increase arousal and counteract passive driving fatigue. A study by Gershon et al. [8] also corroborates the ability of a trivia game to decrease fatigue. Finally, recent research by Bier et al. [3] investigated the gamification of the driving experience to prevent fatigue. Their study used a Wizard-of-Oz approach to conduct voice-based trivia games related to the outside environment. They found that their gamification approach contained upcoming fatigue, similar to verbal communication with a passenger. However, compared to the passenger conversation, the games investigated in this study were directed towards driving, using environmental elements. Therefore, it ensures that the driver focuses more on the driving task than unrelated conversations or games.

Research into how music can affect driving has yielded mixed results. While some research shows that music can increase aggressiveness and distraction, others show that it is an excellent strategy to counteract boredom while driving [4]. Specifically, to counteract passive driving fatigue, music has the potential to be an effective countermeasure. Amirah et al. [1] showed that listening to pop music was associated with a decrease in driving fatigue, reaching a 12% decrease in the 26-44 year age group and 22% in the 20-25 age group. Liu et al. [16] explored a music recommendation system for increasing driver alertness. They created a machine learning algorithm that learned to select the best songs based on EEG data, to improve the alertness of the individual driver. This illustrates that using machine learning to control music selection could increase the effectiveness of music as a measure against fatigue.

2.1.2 In-Car Voice Assistants and driving fatigue. In-car voice assistants allow hands-free interactions with car technologies while keeping their eyes on the road. Large et al. [12] demonstrated the benefits of in-vehicle digital assistants as a countermeasure to passive task-related fatigue. They used a Wizard-of-Oz approach to simulate a conversational agent in a driving context and found it positively affected arousal. The results showed that driving performance improved while participants reported higher alertness and lower sleepiness. Interestingly, participants in the study reported less happiness when driving with a conversational agent, highlighting the importance of developing conversational designs that can reduce fatigue while simultaneously providing a positive user experience.

3 STUDY

In order to investigate how to reduce passive driver fatigue through the increase in arousal, this section presents a 2 (Activity: Music vs. Story) × 3 (Participation: Passive vs. Vocal vs. Active) within-subject study.

3.1 Participants and Materials

We recruited 21 participants (12 male, 9 female; age range: 21-55, mean = 28.9, *SD* = 8.9) using convenience sampling. All participants volunteered, did not receive compensation, and had valid driver's licenses (average driving experience = 9.5 years, *SD* = 8.7).

For safety reasons, we used a driving simulator[1] instead of real-world driving, as the task included engagement with non-driving-related activities. Participants used the City Driving Simulator [6] while wearing an OpenBCI Mark IV electroencephalography (EEG) helmet [21] with the OpenBCI Ganglion board [22]. Additionally, participants wore the Empatica E4 [10] to measure electrodermal activity (EDA). The driving simulation featured a realistic yet monotonous highway with straight roads, minimal curves, and light traffic.

3.2 Measurements

We used the Ganglion bio-sensing device to measure electroencephalography (EEG) with the OpenBCI Mark IV EEG helmet [31] (200Hz). In line with existing research [26, 27], the electrodes were placed in the prefrontal cortex region (F3, F4, AF3, and AF4) following the 10-20 system. We removed frequencies below 3Hz and over 30Hz during data cleaning using a second-order band-pass filter. Subsequently, we conducted a spectral analysis using Welch's method with a four-second window to find the power of each frequency band. In line with Ramirez et al. [26, Equation 1], we calculated arousal using the Beta to Alpha waves ratio. To measure Electrodermal activity (EDA), we used the Empatica E4 wristband [10] (4Hz). The normal range for values is between 1 and 20 microsiemens [10], with higher values indicating higher arousal [11].

Additionally, we collected driving performance metrics (i.e., driving errors and steering wheel reversal rate). Driving performance metrics can reveal driver distractions during each activity and participation mode. To identify a decline in driving performance, we observations indicating cognitive distraction [25]. Specifically: lane deviation (crossing the road line marking), speeding (over 10% above the limit), following distance (keeping a minimum distance of three seconds to the car in front), and averted visual attention (looking away from the road). Two independent observers manually recorded performance metrics during the analysis.

Lastly, we measured the Steering wheel Reversal Rate (SRR) for each participant and each condition of our study. The SRR indicates visual and cognitive overload [17]. In line with Markkula and Engström [17], the angle interval chosen for this study was between 2 to 6 degrees. The SSR represents how many reversals a

[1]We used the Logitech G29 Driving Force Racing Wheel, clutch, break pedals, and G Shifter.

driver performs, on average, per second, with more reversals, being an indication of high cognitive task load.

3.3 Activities and Participation Levels

Our study explored driver arousal through Music and Story interventions, with participants engaging via Passive listening, Vocal (verbal interactions), and Physical (steering wheel inputs) participation modes.

3.3.1 Activity 1: Music. Participants chose four songs, two with familiar lyrics, and we added two more from the top 50 light rock hits of the last three decades, aiming for six songs each. This genre, chosen for its arousal benefits without aggressive driving tendencies [34], was tested in three modes. In Passive listening, they heard a mix of pre-selected and chosen songs. For Vocal participation, they sang along to chosen songs with lyric familiarity, receiving encouragement from the voice assistant (e.g., "Hey driver [name], you are doing awesome, keep listening and singing along.") [24]. In Physical participation, participants tapped the steering wheel rhythmically to a pre-announced song. Songs were played for 2 minutes and 30 seconds, varying the sequence by participation mode.

3.3.2 Activity 2: Story. We adapted three 'Choose your own adventure' stories for experiment length. During the Passive listening condition, the voice agent simply narrated the story. A decision event occurred every 20-25 seconds in the Vocal and Physical conditions. Vocal participants verbally made story choices, while Physical participants made decisions by tapping on the steering wheel, nodding, or shaking their heads, ensuring dynamic interaction with the voice assistant.

3.4 Procedure

Participants were instructed to drive on simulated highway and follow traffic rules and the instructions from the voice assistant to participate in activities.

The session started with a five-minute rest period for participants to adjust their seats and get comfortable, followed by a five-minute familiarisation drive with the simulator to make any needed adjustments. Each condition drive lasted approximately five minutes, with participants following voice assistant instructions for the three conditions. A two-minute driving break between conditions helped reset arousal levels to baseline. The sequence of Activities and Participation levels was counterbalanced to prevent order bias.

4 RESULTS

Our statistical analysis aimed to assess the performance of Activity types concerning their ability to increase arousal to mitigate passive fatigue and the detrimental effects this could have on driving performance. For each arousal (i.e., EEG and EDA) and driving performance (SRR and DPM) metric, we performed factorial repeated measures ANOVA with Activity and Participation level as within-subject variables and demographic data as between-subjects factors.

4.1 Arousal

Repeated measure ANOVA test revealed a significant main effect of Activity type on arousal level as measured by both EEG (F(1,20) = 841.6, $p < .01$, $\eta_p^2 = .97$) and EDA (F(1,20) = 1163.5, $p < .01$, $\eta_p^2 = .98$). For EEG data post hoc comparisons with Bonferroni corrections showed that arousal levels were significantly higher ($p < .01$) during music (M = .29, SD = .009) compared to Story (M = .26, SD = .01) activities. EDA data post hoc comparisons revealed the same pattern in that arousal during Music (M = 7.16, SD = .25) was significantly ($p < .01$) higher compared to Story (M =5.94, SD = .41).

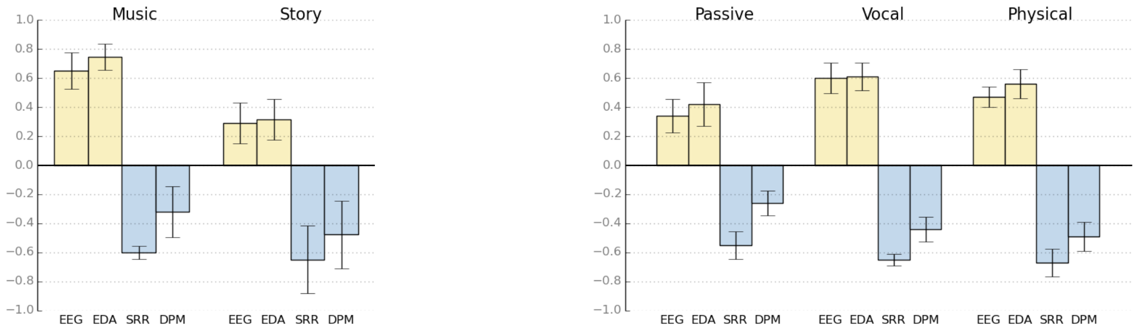
Results also showed significant main effects for Participation levels in both EEG (F(2,40) = 215.4, $p < .01$, $\eta_p^2 = .91$ and EDA (F(2,40) = 69.2, $p < .01$, $\eta_p^2 = .76$) measurements. Post hoc comparisons with Bonferroni corrections showed that arousal levels differed significantly among all participation conditions ($p < .01$). Both EEG and EDA measurements showed that the highest arousal levels were achieved during Vocal, followed by Physical participation and finally, Passive participation (see Table 1 for details). In addition, we found a significant interaction effect between Activity and Participation levels for both EEG (F(1.39,27.9) = 39.4, $p < .01$, $\eta_p^2 = .66$) and EDA (F(2,40) = 21.3, $p < .01$, $\eta_p^2 = .52$). Examination of this interaction effect revealed that when comparing Physical participation with the Passive condition, the increase of arousal was significantly higher in Story compared to the Music Activities.

	Arousal		**Driving Performance**	
Activities	*EEG*	*EDA*	*SRR*	*DPM*
Music	.29 (.01)	7.16 (.25)	.61 (.04)	5.8 (2.1)
Story	.26 (.01)	5.94 (.40)	.65 (.22)	7.7 (2.8)
Participation Level				
Passive	.27 (.02)	6.24 (0.8)	.57 (.18)	5.1 (2.1)
Vocal Participation	.29 (.02)	6.78 (0.5)	.65 (.08)	7.3 (2.4)
Physical Participation	.28 (.01)	6.64 (.06)	.68 (.18)	7.9 (2.6)

Table 1: Results for Arousal (EEG and EDA) and Driving Performance (SRR and DPM) measurements for the two activities and three participation levels.

Finally, we performed mixed model repeated measures ANOVA tests with age, gender, driving experience, and driving frequency as between-subjects factors to investigate whether those demographic variables influenced arousal responses to our activities. However, results showed no significant interaction effects of demographic categories on arousal responses to the Activity types or Participation levels.

Next, we analysed how activities and participation affect driving performance. Similarly to the previous analysis, we conducted repeated measures ANOVA tests for SRR and DPM measurements. In this case, however, higher scores indicated worse driving performance for both metrics. Results show that even though SRR was higher during Story than Music, there was no significant main effect of Activity ($p = .12$). But there was a significant main effect of Participation level (F(2,40) = 7.35, $p < .01$, $\eta_p^2 = .27$) on steering reversal rate. Participants performed worse during the condition of Physical (M = .68, SD = .18) followed by Vocal (M = .65, SD = .08) and Passive



(a) Music vs Story. The chart shows averaged values for all participation levels.

(b) Passive listening, Vocal participation, and Physical participation. The chart shows averaged values for both activities.

Figure 1: Summary results. Yellow bars represent arousal levels, and blue bars show a decline in driving performance. Data have been normalised to allow for comparing metrics that utilise different scales. Error bars show standard deviations.

participation (M = .57, SD = .18). Post hoc comparison with Bonferroni corrections revealed driving performance differed significantly only between the Passive condition and those of Physical (p = .01) and Vocal (p = .02) participation. Mixed model repeated measures ANOVAs did not reveal any significant main or interaction effects between SRR and demographic categories.

4.2 Driving Performance Metrics (DPM)

DPM was the added frequency of observations (Section 3.2) of all deviations from optimal driving. Subsequently, we performed repeated-measures ANOVA with overall DPM as the dependent variable while Activity and Participation level were the within-subject independent variables. Results showed statistically significant differences in deviations from optimal driving performance both for Activity (F(2,40) = 26.36, $p < .01$, $\eta_p^2 = .57$) and Participation level (F(2,40) = 18.29, $p < .01$, $\eta_p^2 = .48$). Driving performance was considerably worse during the Story (M = 7.7, SD = 2.8) than during Music (M = 5.8, SD = 2.1). Also, drivers performed worse during Physical (M = 7.9, SD = 2.6), followed by Vocal (M = 7.3, SD = 2.63), and finally Passive (M = 5.1, SD = 2.1) participation. Post hoc comparisons with Bonferroni corrections show that differences in driving performance were significant apart from those between Physical and Vocal participation. The Mixed model repeated measures ANOVA, including demographic variables as factors, showed no significant results.

5 DISCUSSION

Our findings indicate that Music activities are significantly more effective than Story activities, offering higher arousal with less impact on driving performance. We also observed that varying participation types could amplify stimulation, though this came at a cost to driving performance (see Figure 1) This section explores the implications for designing in-car voice assistants to combat driving fatigue and introduces a real-world application scenario.

5.1 Activities and Participation Levels

Activity - EEG and EDA data indicate Music as the better activity for increasing arousal across all participation levels, with a minimal impact on driving performance, confirming its potential as a passive fatigue countermeasure [1, 15, 34]. Although Story increased arousal, it was less effective than Music and more distracting. It would be interesting to explore how to develop a Story design similar to that suggested by Bier [3]. In this context, the interactive Story would use the driving environment as part of the game flow rather than creating additional cognitive load. Furthermore, advances in large language models offer exciting opportunities to create immersive, interactive stories, enhance in-car voice assistant capabilities, and meaningfully engage drivers.

Participation Level - Our analysis showed significant differences in arousal across participation levels, highlighting how active task engagement could boost driver stimulation and arousal. This suggests that in-car voice assistants could dynamically tailor their guidance to maximise arousal against passive fatigue. Should an activity fall short in increasing driver arousal, the assistant could adjust its suggestions to more effective alternatives. Prior research indicates that persuasive feedback from voice assistants can increase engagement [24]. Employing such feedback, voice assistants can motivate drivers to stay actively involved in suggested activities, acting as both a supportive and motivational presence.

5.2 Application scenarios

Our vision promotes using in-car voice assistants for preemptive and reactive mitigation of passive driving fatigue. These systems aim to preemptively identify monotonous driving stretches, offering stimulating activities to maintain driver engagement and alertness, which are crucial for road safety. Moreover, passive fatigue remains a concern in the transition to partially automated vehicles; these assistants can help maintain driver alertness, even when automation allows engagement in non-driving tasks [9]. Monitoring arousal and suggesting activities upon detecting diminished alertness ensures attentiveness for control takeover in automated vehicles. This study explores interventions against passive fatigue, with future research expected to refine the balance between arousal and driving performance. Advancements in technology, particularly large language models, introduce new interactive capabilities for in-car systems, suggesting a future where voice assistants significantly enhance driver safety.

5.3 Limitations

Our study,was conducted using a simulator, which limits how our findings can be applied to real-world driving. Additionally, we did not involve fatigued participants, focusing instead on the effectiveness of various auditory activities in increasing arousal without impairing driving performance.

6 CONCLUSION

Our research focused on leveraging in-car voice assistants to alleviate driver fatigue by recommending auditory interventions that help stimulate drivers and help maintain their alertness. Our exploration of different activities revealed that music emerged as the most promising intervention, primarily due to its favourable arousal-to-distraction ratio. While interactive stories were also effective, they exhibited a slightly less favourable ratio. Additionally, we showed that the stimulation effect of those activities can be further modified by engaging drivers in vocal or physical participation. The objective of our study extended beyond the immediate findings, aiming to inspire further research in leveraging voice assistance to alleviate driver fatigue and enhance road safety.

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