https://doi.org/10.21872/2024IISE_7993

Proceedings of the IISE Annual Conference & Expo 2024
A. Brown Greer, C. Contardo, J.-M. Frayret, eds.

Police In-Vehicle Technology Adaptation Based on Officer Cognitive State

Chihab Nadri, Jia Deng, Ashutosh Chauhan, David Wozniak, Maryam Zahabi
Wm Michael Barnes '64 Department of Industrial & Systems Engineering
Texas A&M University
College Station, TX, USA

Abstract

Law Enforcement Officers (LEOs) experience high levels of workload and stress while on duty. LEO cognitive state varies under different driving conditions, such as patrol, pursuit, and emergency driving. In-vehicle interfaces further increase LEO workload, as LEOs need to process information from the mobile computer terminal and radio, creating a need for adapting information intake under high workload. To address this need, this study introduces a system designed for real-time adaptation of in-vehicle technology for LEOs based on their cognitive state. The system leverages real-time data to track and manage the workload dynamically. Gaze behavior analysis is utilized to determine attention allocation during various driving scenarios. Sensory outputs are monitored to assess physiological measures of workload. Additionally, vehicle dynamics data provide insights into driving behavior under different driving conditions. Based on the live processing of these variables, the system adjusts the in-vehicle interface and information delivery based on the LEO's cognitive state. The system is intended to optimize the interaction between the officer and in-vehicle technology, resulting in better performance and optimizing workload levels. The proposed system could offer a novel approach to integrate context-aware technology into police vehicles. This approach aims to contribute to the field of live information processing and human-system interaction, and more broadly contributes to the advancement of adaptive technologies in high-stress professional environments.

Keywords
Adaptive system, workload, driver performance, law enforcement.

1. Introduction
Law Enforcement Officers (LEOs) must contend with several tasks requiring in-vehicle technology while driving, from cell phones and dispatch radios to interaction with the mobile computer terminal (MCT). This multitasking increases cognitive workload and the risk of motor vehicle crashes (MVCs), representing one of the leading causes of line-of-duty deaths for LEOs (National Law Enforcement Memorial Fund, 2021).

LEOs face distinct challenges in their work due to the use of in-vehicle technologies. Research has indicated that the MCT and radio are among the most important and frequently used in-vehicle technologies for LEOs AR. These technologies, while essential, significantly increase the risk of distraction and cognitive overload. This effect is more pronounced in novice LEOs (nLEOs), who possess less experience to handle multitasking and the use of these technologies (Park, Wozniak, & Zahabi, 2024). To address these challenges, our research team sought to develop adaptive technology and modify MCT interface to reduce cognitive load.

Adaptive systems are designed to automatically adjust their operations in response to the user's current state and the surrounding environment, thus enhancing performance and safety (Zahabi & Abdul Razak, 2020). In the context of law enforcement, this means creating a system that can intelligently alter the flow of information to an officer based on their cognitive load and driving conditions. Such systems utilize advanced algorithms and sensors to monitor various indicators of the officer's state, such as eye movement, heart rate, and even brain activity, to gauge their level of focus and stress. By doing so, the system can prioritize critical information during high-stress scenarios, such as pursuits or emergencies (Zahabi et al., 2023), and reduce informational clutter during lower-stress periods. This dynamic adjustment could maintain the officer's cognitive load at an optimal level, ensuring that they remain alert to their environment and are better prepared to make quick, informed decisions.

In this study, we describe an adaptive in-vehicle technology system specifically tailored for LEOs. Our methodology involves using a cognitive performance model that is trained on nLEOs (Wozniak, 2023). This model is then

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combined with an augmented reality head-up display (AR-HUD) MCT which can display information to LEOs on the windshield of their car, avoiding repeated glances away from the road. We test the validity of our approach and training system through a pilot study by recruiting four participants to go through a series of simulated driving scenarios. The driving scenarios involve either low or high workload inducing conditions, such as pursuit driving and use of in-vehicle technology. The results of the pilot study seek to inform our design and identify if the adaptive system activates in conditions of high workload and if the simulated driving conditions induce workload increases.

2. Methodology

2.1. Adaptive workload classification system

The system is based on the processing of workload data to assess real-time workload levels and display simplified LEO information when users experience high workload. The adaptive system consists of three components (Zahabi & Abdul Razak, 2020):

- Adaptive Input Measures: The system uses physiological variables in the form of heart rate and skin conductance variables collected from an Empatica E4, and pupil information collected by a Pupil Labs Eye Tracker (as seen in Figure 1). Empatica E4 variables include the root mean squared of successive differences between normal heartbeats (RMSSD), Skin Conductance Response (SCR) and electrodermal activity (EDA). Pupil data includes blink rate and percentage change in pupil size (PCPS).
- Adaptive Logic: The machine learning algorithm is trained on data collected from a naturalistic study involving 24 nLEO participants during patrol operations (Wozniak, 2023), where the aforementioned physiological measures were recorded. The model used Random Forest as the adaptive logic. This method was found to be more accurate that other algorithms such as Random Fourier Features or Support Vector Machines.
- Adaptive Variables & System Response: Upon determining an officer's cognitive workload, the system adjusts the AR-HUD MCT's display accordingly. When the machine learning algorithm classifies the workload as high, the AR-HUD MCT responds by simplifying the displayed LEO information. This simplification process is designed to reduce cognitive load by presenting only the most critical information in a clear and concise manner, thereby mitigating the risk of information overload, and ensuring that officers can maintain focus on their primary tasks. The criteria for simplified information are predetermined based on operational priorities and the need for quick, decisive action under stress.

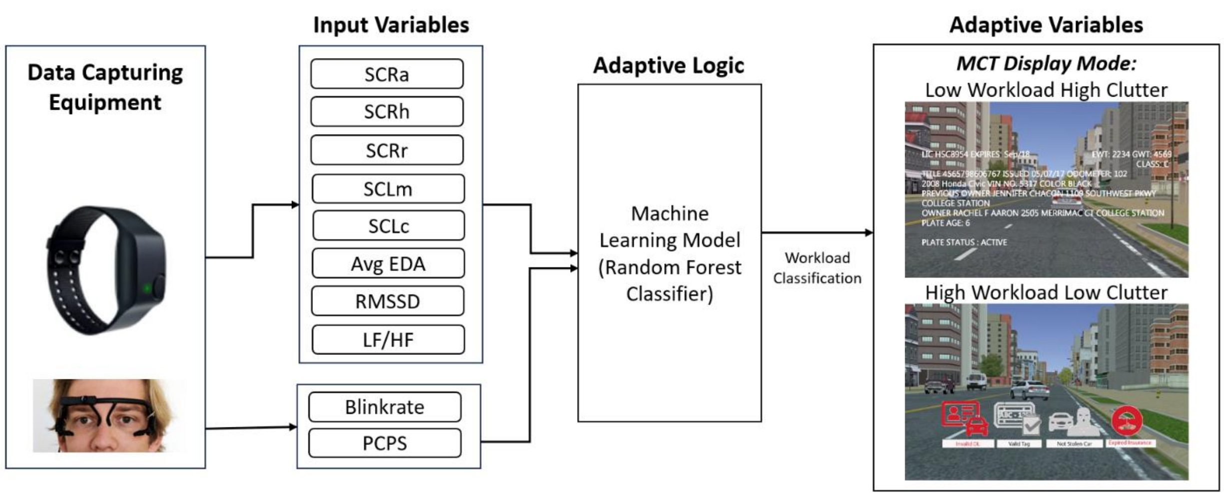

Figure 1: Adaptive workload classification system, taking physiological variables as input, applying Random Forest as the adaptive logic, and displaying either high or low clutter displays based on workload levels. (Note: SCR – Skin conductance, a – amplitude, h – half recovery time, r – rise time, SCL – Skin Conductance Level, m – mean, c – change, EDA – ElectroDermal Activity, RMSSD – root mean squared of successive differences, LF/HF – Low Frequency/High Frequency, PCPS – percentage change in pupil size, MCT – Mobile Computer Terminal).

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2.2. AR-HUD MCT

The adaptive workload classification system consisted of an augmented reality (AR) display that would adapt dynamically to user workload to display MCT information in the line of sight. When detecting low workload, the AR-HUD MCT would display high clutter information that is similar to what LEOs see in their MCT (as seen in Figure 2-a). If workload levels are high, the AR-HUD MCT would display a simplified version of this information with low clutter focusing on the most relevant aspects to the task at hand (as seen in Figure 2-b). The low clutter display includes the most critical pieces of information (i.e., driver license status, vehicle status, insurance status) that LEOs need before stopping a vehicle (Zahabi & Kaber, 2018).

Figure 2: Adaptive AR-HUD MCT display showing a) Regular MCT information for low workload; and b) Simplified MCT information for high workload with low clutter.

2.3. Pilot Study

The pilot study involved four participants, approved by the Institutional Review Board (IRB), and utilized a fixed-based driving simulator equipped with a 60 Hz sampling rate for driving data. Additional tools were used for physiological data collection, including the Pupil Labs Eye Tracking glasses for pupillometry and the Empatica E4 wristband for heart rate and skin conductance monitoring. A laptop simulating the current MCT setup in police vehicles was also used and placed beside participants. Participants were non-LEOs for this pilot study. This was deemed appropriate as our model was trained on nLEOs who were also not experienced with MCTs.

Participants engaged in eight simulated urban driving scenarios under moderate traffic conditions, adhering to a 40-mph speed limit. In pursuit driving conditions, participants were instructed to follow a vehicle at a speed of 60-mph. The simulations were designed to replicate both normal and pursuit driving conditions consistently across all trials to maintain a constant difficulty level and environmental conditions.

The driving tasks included a plate number check task and a radio communication task, both aimed at mimicking real-life police duties. These tasks required participants to interact with the MCT and respond verbally to questions about the tasks, thereby evaluating their ability to manage driving alongside secondary tasks.

The experiment followed a 2x2x2 design, comparing the adaptive AR-HUD MCT against current technology under various conditions: 1) normal patrol vs. pursuit driving, 2) with or without a secondary task, and 3) with the adaptive system on or off. This design aimed to assess driving performance (lane deviation, speed deviation, steering entropy), and workload (changes in pupil size, heart rate variability, and subjective assessments).

Participants underwent initial training to familiarize themselves with the simulator, followed by a familiarization scenario incorporating the tasks to be performed during the actual experiment. The study calibrated and recorded baseline physiological responses before proceeding with the randomized driving scenarios. Upon completion, participants were interviewed to gather their perspectives on the adaptive display system. Data were collected through all drives, with drives where speed deviation exceeding 9mph being excluded from data analysis, as participants were not abiding by the speed limit specified for the study.

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3. Results

Descriptive data comparing workload levels in drives with the adaptive display system turned on show that the low clutter MCT display was activated at times drivers experienced higher workload (Table 1). This was observed for driver activity load index (DALI) workload scores, as well as physiological referents: higher PCPS and blink rate are associated with higher workload, and similarly lower RMSSD also are linked to higher workload.

Table 1: Mean values of driving, physiological, and workload variables for driving sections where the adaptive system is inactive and active.

	Independent Variable	**Lane Offset**	**Speed deviation**	**RMSSD**	**PCPS**	**Blink rate**	**DALI**	**Steering Entropy**
Adaptive System Activation	*High Clutter MCT*	0.32	3.35	0.75	17.15%	13.16	50.48	0.59
	Low Clutter MCT	0.30	4.62	0.33	20.34%	20.16	67.06	0.49

For drives that used the adaptive display system, the low clutter display (used in high workload conditions) was active more often in pursuit driving conditions and when the secondary task was activated (Figure 3).

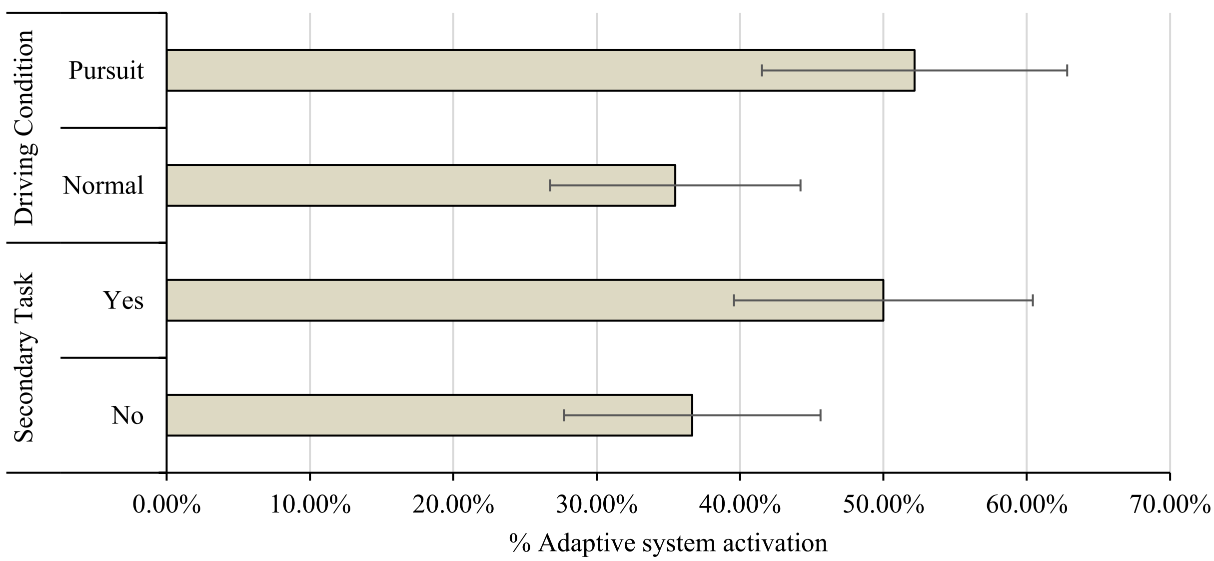

Figure 3: Average percentage likelihood of the activation of the simplified low clutter AR-HUD MCT by the adaptive system under different conditions. Error bars represent standard error.

Additionally, the low clutter display suited for high workload became active most often with the combination of pursuit driving with secondary task activation, at an incidence rate of 66.67% (as seen in Table 2). Activation for normal patrol driving with no secondary task was lowest, whereas pursuit driving with no secondary task and regular patrol driving with a secondary task each saw an increase in activation when compared to regular patrol with no secondary task.

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Table 2: Mean incidence rate of the low clutter display for manipulated variables.

Driving Condition	Secondary Task	Low Clutter Display Activation %
Normal	No	31.25%
Normal	Yes	40.00%
Pursuit	No	42.86%
Pursuit	Yes	66.67%

Descriptive data of the interaction and effect of driving condition, adaptive system activation, and secondary task (Table 3) show the adaptive system does not substantially influence steering wheel angle and steering entropy. In terms of lane offset, we observe a similar effect, except for pursuit driving with the secondary task activated where lane offset is reduced when the adaptation is turned on. In terms of speed deviation, we observe no significant change for most driving situations except for the pursuit driving and secondary task situation. There, speed deviation is reduced when the adaptive system is activated. The findings suggest that the adaptive system might be effective in improving driving performance in high demand situations (i.e., during pursuit driving conditions and when using secondary tasks).

Table 3: Mean values of driving performance for manipulated variables. Darker color refers to increasingly challenging situations, with the darkest color being used for the combination of pursuit driving and the presence of the secondary task.

		Secondary Task			
		No Secondary Task		**Secondary Task Present**	
Driving Condition	**Driving Performance**	**Non-Adaptive System**	**Adaptive System**	**Non-Adaptive System**	**Adaptive System**
Normal	Speed Deviation	3.46	3.26	4.74	4.34
	Steering Wheel Angle	0.05	0.06	0.05	0.04
	Steering Entropy	0.51	0.51	0.56	0.61
	Lane Offset	0.30	0.32	0.34	0.40
Pursuit	Speed Deviation	3.88	4.15	4.76	3.88
	Steering Wheel Angle	0.07	0.06	0.05	0.03
	Steering Entropy	0.50	0.50	0.58	0.61
	Lane Offset	0.32	0.30	0.42	0.19

4. Discussion

While our sample size was small, we observed cognitive load increases in pursuit driving conditions and with the introduction of a secondary task. These results line up with previous work in the field regarding LEO workload (Zahabi et al., 2023). Results indicate the activation of the low clutter display occurred more often in these conditions, pursuit driving and secondary task activation, of high workload. Both subjective workload and physiological data from drives with the adaptive system (Table 2) also indicate workload was high when the display switched from regular MCT to the low clutter AR-HUD MCT. These findings support the idea that our system is able to detect high workload and switches displays as it occurs.

Additionally, the highest incidence rate for the low clutter display was observed when both pursuit driving and secondary task presence were active. Minor increases were observed when only pursuit driving was the active situation, and when regular patrol driving was active, and a secondary task was required. This seems to suggest that the combination of pursuit driving and secondary task activation was significant in overwhelming participants' capabilities, and as such workload increased significantly.

In comparing drives with the adaptive system AR-HUD MCT with regular drives, we observe that participants exhibit better driving performance in certain driving situations with the adaptive display system than in the non-adaptive condition. This was the case for pursuit driving with an active secondary task, which was also the situation with the highest levels of workload identified by the adaptive system (Table 2). While changes in steering wheel angle and steering entropy were not identified, reductions in speed deviation and lane offset suggest the adaptive system is effective in improving driving performance in high demand situations. This is particularly relevant as our pilot study sample consisted of a non-LEO sample unfamiliar with LEO tasks.

Participants in this pilot study frequently mentioned their unfamiliarity with the MCT tasks and difficulty ascertaining the content of radio communications coming in. These communications were based on realistic conversations between LEOs. These aspects might suggest that the recruitment of a wider sample of LEOs familiar with patrol tasks will shed more light on the influence of our system on driving performance.

5. Conclusions

This study introduced an adaptive system designed to alter in-vehicle technology for LEOs in real-time, based on their cognitive states. Through the analysis of workload levels in the pilot study, the system was capable of dynamically adjusting the in-vehicle interface when participants experienced heightened levels of workload. Additionally, driving performance results suggest the adaptive system might benefit LEOs in high workload adversarial conditions, specifically in pursuit driving while multitasking with radio communications or using the MCT. These preliminary findings indicate a promising avenue for future exploration, with plans to further assess the system's effectiveness in real-world settings with LEOs and explore more advanced machine learning algorithms.

The objective of this study was not only to address the immediate need for reducing information overload and stress in high-stress driving scenarios but also to contribute to the broader field of adaptive technologies within high-stress professions. The positive outcomes from the pilot tests underscore the potential of context-aware technologies to significantly impact the efficiency and safety of LEOs in the field.

Acknowledgements

Funding for this research was provided by the National Science Foundation (No. IIS-2041889). The views and opinions expressed are those of authors.

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