MODELING AND ANALYSIS OF ADVANCED DRIVER ASSISTANCE

SYSTEMS IN POLICE VEHICLES

A Dissertation

by

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ABSTRACT

Motor vehicle crashes (MVCs) involving police vehicles have been identified as a significant problem nationwide. Police MVCs are attributed to driving at high speed, pursuit situations, extreme weather conditions, complex traffic situations, and interacting with in-vehicle non-driving related tasks (NDRTs). Advanced driver-assistance systems (ADAS) are promising technologies to enhance officers' safety by relieving them from some driving related activities. This study aimed to examine whether ADAS technologies could enhance officers' driving performance, decrease their workload, and increase their trust in vehicle safety. The research methodology included a literature review, survey with law enforcement officers (LEOs), driving simulation study, and models of officers' reaction times for steering and braking.

Initially, a systematic review of the existing and upcoming ADAS features in police vehicles was conducted. Based on the findings, a survey study with 73 police officers was conducted (Chapter 2) to understand their needs regarding ADAS in police vehicles. Results suggested that ADAS such as forward collision warning (FCW), blind spot monitoring (BSM), and automatic emergency braking (AEB) could be beneficial features for police vehicles. Additionally, results of the correlation analyses indicated that officer behavior and opinion on ADAS features were influenced by the trust officers had in the available ADAS systems among other key factors such as ADAS training and perceived usefulness. Technology acceptance modeling (TAM) results suggested that training on ADAS could enhance officers' perception of the features and increase their intention to use them. However, officers identified several obstacles to the adoption of

ADAS, including lack of adaptability, usability issues, and distrust in the technology. To promote the use of ADAS, officers recommended having adaptive ADAS warnings tailored to specific driving situations, such as pursuit driving and engagement in an NDRT.

Based on the results of the survey study, a driving simulator study was conducted to examine how FCW/AEB and BSM impact the driving performance, workload, and trust of officers (Chapter 3). The findings of the simulator study indicated that FCW and AEB improved driving performance, while the impact of BSM was limited due to its low salience. ADAS warnings increased drivers' workload up to a certain point, enhancing their passing performance. However, during pursuit situations, officers' driving performance degraded, and their cognitive load increased, emphasizing the need for ADAS that can help maintain their situational awareness. The study also developed predictive models to estimate police officers' brake reaction time and steering wheel angle during critical driving situations. The results can be used as inputs for an adaptive FCW system.

The findings of this study can be used to improve the design of ADAS technologies, which can improve the safety of LEOs and reduce the risk of crashes during high-demand driving situations.

DEDICATION

I am grateful beyond words for the unwavering love and support that my parents have bestowed upon me throughout my academic journey. I also extend my heartfelt thanks to my aunts for their unceasing encouragement through their prayers. I am deeply appreciative of the support and encouragement of my friends, particularly Tiger, during my PhD.

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NOMENCLATURE

ACC	Adaptive cruise control
ADAS	Advanced driving assistance systems
AEB	Autonomous emergency braking
ANPR	Automatic number plate recognition
ATIS	advanced traveler information systems
AVE	Average variance extracted
BSM	Blind spot monitoring
CC	Cruise control
CDF	Cumulative distribution function
CPR	collision prevention rate
CSW	Curve speed warning
CW	Pedestrian crash avoidance/ mitigation
DALI	Driving load activity index
DRT	Detection response task
E.g.	For example
FCW	Forward collision warning
GHR	The Grazis, Herman, and Rothery
HRV	Hear rate variability
IMA	Intersection movement assist (IMA)
TTC^{-1}	Inverse time to collision
IRB	Institutional review board
LEO	Law enforcement officer
LK	Lane keeping assistance
M	Mean
MCT	mobile computer terminals

Mph	Miles per hour
MVC	Motor vehicle crash
NDRT	Non-driving related task
OED	Object and event detection
PCPS	Percentage change in pupil size
PEU	Perceived ease of use
PLS-SEM	partial least square structural equation modeling
PU	Perceived usefulness
RMSE	Root mean square error
RMSSD	Root mean square of successive difference between normal heartbeats
RSME	Rating scale mental effort
SD	Standard deviation
SRMR	Standardized root mean square residual
TAM	Technology acceptance modeling
TPB	Theory of planned behavior
TTC	Time to collision
UTAUT	Unified theory of acceptance and use of technology

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1. INTRODUCTION*

1.1.Police vehicle crash rates

Motor vehicle crashes (MVCs) involving emergency vehicles, such as police vehicles, fire trucks, and ambulances, have been identified as a significant problem nationwide (Savolainen et al., 2009). The number of crashes among law enforcement officers (LEOs) was found to [1]be higher than other emergency vehicles. The national safety council (NSC) reported 138 deaths in fire trucks, 252 deaths in emergency medical service vehicles, and 805 fatalities in police car crashes from 2010 to 2018 (NSC, 2018). In another investigation, Maguire et al. (2002) found that the number of fatalities among police officers was 2.5 times higher than the national average among all occupants in the U.S. from 1992 to 1997. According to national law enforcement officers memorial fund (NLEOMF), more than 1700 law enforcement deaths were reported from 2011–2020, with 21% of these fatalities attributed to the MVCs (NLEOMF, 2021).

High number of crashes among police vehicles might be related to driving at high speed, pursuit situations, extreme weather conditions, and complex traffic situations (Zahabi et al., 2021b). Variables linked with dangerous police behaviors during pursuit situations include speeding and losing full control of the vehicles (LEOs' or suspect's vehicle), violation of traffic rules, passing or changing lanes inappropriately, improper right/left/U-turn, distracted driving, and driving in an unsafe car-following distance (Chu, 2016). Additionally, the potential risks for police officers being distracted while

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driving in pursuit situation was found to increase the probability of crashes causing injuries (Yager et al., 2015).

Police vehicles are equipped with in-vehicle technologies such as mobile computer terminals (MCTs), radio, video cameras, radar, and sirens. Using in-vehicle technologies while driving was found to cause officer's distraction and increase the risk of MVCs (Chu, 2016). Surveys of LEOs have indicated that the MCT is the most important and most frequently used technology for officers while driving (Zahabi & Kaber, 2018b). Findings of naturalistic driving studies also suggested that MCTs are the most cognitively and visually-demanding in-vehicle technologies among police officers (Shahini et al., 2020a; Zahabi et al., 2021b). Therefore, it is necessary to reduce driver distraction caused by MCTs to decrease the probability of crashes and number of fatalities among LEOs.

1.2. Advanced driving assistance systems

Society of automotive engineers provides a taxonomy of the levels of driving automation, which ranges from level 0 (no driving automation) to level 5 (full driving automation). ADAS refer to level 1 (driver assistance) in this taxonomy (SAE, 2021). ADAS are vehicle control technologies that enhance driving comfort and traffic safety by using vehicle sensors (e.g., radar, laser, camera) to help drivers identify and react to potentially hazardous traffic situations (Gietelink et al., 2006).

One promising method of reducing driver distraction and number of crashes is use of ADAS technologies such as forward collision warning (FCW), AEB, lane keeping assistance (LK), blind spot monitoring (BSM), adaptive cruise control (ACC), and autonomous parking assistance systems (Shaout et al., 2011). Previous studies found that ADAS have a potential to improve driver safety by reducing the crash severity and number of crashes (Cicchino, 2017a; Fildes et al., 2015; Isaksson-Hellman & Lindman, 2016). In addition, ADAS can relieve drivers from some driving-related activities, letting them get engaged in a non-driving related task (NDRT), and mitigate driver stress (Nasr et al., 2021). Table 1.1 provides a list of common existing ADAS features in vehicles with their description.

Table 1.1. Existing ADAS features.

ADAS feature	Description
ACC	It automatically adjusts the speed of vehicle to keep a safe distance from vehicles ahead (Marsden et al., 2001).
Automotive night vision	It uses a thermographic camera to improve drivers' perception and visual distance in darkness or poor weather beyond the reach of the vehicle's headlights (Martinelli & Seoane, 1999).
AEB	It uses sensors around the vehicle to recognize potential collisions to intervene or brake on behalf of the driver to prevent crashes (Hulshof et al., 2013).
BSM	It uses vehicle-based sensors to detect other vehicles located to the driver's side and rear (blind spot) and warns them to prevent collisions (Cicchino, 2018).
Cruise control (CC)	It automatically maintains a steady speed as set by the driver (Venhovens et al., 2000).
Curve speed warning (CSW)	It uses global positioning system (GPS) information and digital maps to warn drivers when they are approaching a curve or exit on the road with high speed (Chowdhury et al., 2020).
Electronic stability control	It is an automated technology that improves a vehicle's stability by detecting and reducing loss of traction (Farmer, 2006).
FCW	It alerts the driver if they are distracted and fail to brake in case of a sudden hazard such as a decelerating lead vehicle (Yue et al., 2021).

Table 1.1. Existing ADAS features continued.

ADAS feature	Description
Intersection movement assist (IMA)	It warns the driver of a vehicle when it is not safe to enter an intersection because of high collision probability with other vehicles at stop signs or traffic signal signs (Wu et al., 2018a).
Lane keeping assistance (LK)	It warns the driver and helps to keep the car in its lane without driver input (Sentouh et al., 2018).
Parking assistance systems	It uses ultrasonic sensors on front and rear bumpers of the vehicle to detect the obstacles when parking and warn the drivers. It is also integrated with a rear camera to provide visual assistance while parking (Kokolaki et al., 2013).
Pedestrian crash avoidance/ mitigation (PCAM)	It uses sensors and artificial intelligence technology to detect pedestrians and bicycles in an automobile's path to take action for safety (Yanagisawa et al., 2014).
Rear-view camera	It is a special type of video camera that is attached to the rear of a vehicle to aid in backing up and avoid a backup collision (Cicchino, 2017b).
Traffic sign recognition system	It guarantees that the current speed limit and other road signs are displayed to the driver on an ongoing basis (Estable et al., 1994).

Previous studies demonstrated the positive effects of ADAS features on civilian drivers' safety. A report including data from 22 U.S. states during 2010–2014 revealed that rear-end striking crash involvements were reduced by 27% with implementation of FCW alone, 43% with low-speed AEB alone, and 50% with both (Cicchino, 2017a). It is expected that if all vehicles were equipped with FCW and AEB, almost 1 million US rear-end police reported crashes and 400,000 crashes with injuries could be prevented each year (Cicchino, 2018). In addition, test-track results from Fitch et al. (2014) suggested that middle-aged drivers reacted more quickly to a lateral crash threat when BSM warning is activated, and drivers preferred to receive the BSM alert. It is estimated that if all US vehicles were equipped with BSM technologies, about 20,000 injuries and 393 serious crashes could be prevented annually (Jermakian, 2011).

1.3. Advanced driver assistance systems in police vehicles

A review by Nasr et al. (2021) found that current ADAS features in police vehicles include but not limited to BSM, AEB, ACC, PCAM, CSW, FCW, rear-view cameras, automotive night vision, and LK assistance. Table 1.2 categorized the existing ADAS features based on the vehicle model. In addition, Nasr et al. (2021) recommended to equip police vehicles with intersection movement assist (IMA), traffic sign recognition system, left turn assist, evasive steering system, wrong way alert, lane-ending detection, traffic jam assist, facial recognition, automatic number plate recognition (ANPR), and gunshot detection systems to improve officers' safety while driving.

Table 1.2. Existing ADAS features in police vehicles.

ASAS Feature	Ford	Chevy	Dodge
BSM	Yes	Yes	Yes
Bluetooth/Uconnect systems	Yes	Yes	Yes
Rear-View Camera	Yes	Yes	Yes
Pre-Collision Assist	Yes	Yes	No
PCAM	Yes	Yes	No
AEB	Yes	Yes	Yes
LK Assistance	No	Yes	No
Lane Departure Warning	No	Yes	No
Patented Safety Seat	No	Yes	No
FCW	Yes	Yes	Yes

ADAS are promising technologies to enhance officers' safety, efficiency, and communication by relieving them from some driving tasks and letting them be engaged in NDRTs. However, no previous studies investigated the effects of ADAS technologies specifically in police vehicles.

1.4. Research gaps and objectives

This study aims to fill several research gaps in the literature. The first objective of this study is to understand police officers' opinions and needs regarding ADAS in police vehicles and how officer acceptance of ADAS is influenced by different factors. To achieve this objective, an online survey was conducted to assess the effects of different factors including trust, perceived usefulness, perceived ease of use, ADAS training, and demographic information of police officers on their intention to use ADAS using the technology acceptance modeling (TAM). Chapter 1 includes the description of the TAM and the results of the survey.

The second objective of this study is to conduct a driving simulator study to investigate the effects of ADAS technologies on officers' driving performance and workload. The results from the survey study and TAM were used to determine the experimental design and measurements in the simulator study. Although previous studies have focused on the effects of automated driving technologies on civilian drivers, this study aims to investigate the LEO population who are prone to riskier driving situations than civilian drivers. Using both driving performance and workload measures provide a holistic view of the effects of ADAS on LEOs. Chapter 2 further expands the details about the background and the methodology used in the driving simulator study.

The third objective of this research is to build predictive models to predict brake reaction time and steering wheel angle when driving with FCW/AEB and BSM respectively. Chapter 3 further explains the model assumptions and procedure. The results from this model can assist vehicle and vehicle manufacturers to produce adaptive ADAS features and issue an alert whenever it is necessary.

2. SURVEY STUDY*

2.1. Introduction

2.1.1. Technology acceptance model

Theories of human behavior such as technology acceptance modeling (TAM), theory of planned behavior (TPB), and unified theory of acceptance and use of technology (UTAUT) have been used to study technology acceptance among users. Among its wide adoption in all fields of technology acceptance, TAM was found to outperform TPB and UTAUT to model driver acceptance in terms of Behavioral Intention to use ADAS (Rahman et al., 2017). The TAM consists of several variables which explains behavioral intentions and the use of technology (e.g., perceived usefulness, perceived ease of use, and attitudes toward technology), and has been extended by other variables including self-efficacy, subjective norms, and facilitating conditions of technology use (Schepers & Wetzels, 2007). TAM has gained a great consideration mainly because of its transferability to different contexts and its potential to explain the variance in the use of technology and intention to use. Another advantage of TAM is its simplicity of specification with structural equation modeling frameworks (King & He, 2006; Marangunić & Granić, 2015). Researchers have also suggested factors outside of TAM [2]that can affect behavioral intention to use ADAS. Examples of these factors include trust (Ghazizadeh et al., 2012; Najm et al., 2006), which is defined as "the attitude that an agent will help achieve an individual's goals in a situation

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characterized by uncertainty and vulnerability" (Lee & See, 2004), and training. Training has been found as one of the most important factors that contributes to greater user acceptance and system success (Scherer et al., 2019). Coughlin and D'Ambrosio (2012) and Koustanaï et al. (2012) suggested that training can lead to a better system understanding, including system capacities, benefits, and limitations, and therefore, it can affect drivers' behavioral intention to use. In addition, previous studies have suggested that training can influence ease of use of information technology (Davis, 1989). Biassoni et al. (2016) investigated the effects of training with advanced collision warning systems on ADAS technology acceptance with 527 novice drivers. Results indicated that the quantity and quality of information on technology features can significantly change the initial acceptability of the safety device. In addition, pleasantness of use and perceived benefits for safety were found to be the most critical factors for novice drivers. Previous studies paid specific attention to the area of trust in information technology. It is widely accepted that users who trust in certain technology put themselves in a vulnerable position, and the trust relation might lead the user to take the potential risk of losing something important and instead using the technology (Mayer et al., 1995). For example, Xu et al. (2010) developed a TAM model to analyze why travelers accept or refuse advanced traveler information systems (ATIS) and to explain, predict, and increase travelers' acceptance of ATIS. They concluded that trust in ATIS significantly determines travelers' intention to accept and use it (Xu et al., 2010).

2.1.2. Research gap and objectives

There are several differences between civilian driving conditions and police driving conditions, such as the higher demand driving situations police officers are faced with and the frequent use of non-ADAS in-vehicle technologies such as dispatch radios and MCTs. Police officers may override roadway regulations in pursuit situations (Zahabi & Kaber, 2018b), and therefore the ADAS that aid drivers in normal driving conditions can become useless or even a hindrance if they cannot be powered off easily. In addition, potential ADAS must account for technology and equipment unique to police vehicles such as MCTs, further complicating the process of implementing ADAS in police vehicles. To better equip police officers to deal with the increased risk of accidents associated with their profession, it is necessary to investigate ways to improve ADAS use for police vehicles specifically as opposed to civilian drivers in general.

In our prior study, a list of the most prevalent ADAS available for police officers was identified based on a review of literature on police vehicles, patents, and review of scientific research studies (Nasr et al., 2021). Some of the features include rear view cameras, emergency braking, adaptive cruise control, etc. A complete list of these features is provided in Nasr et al., (2021). The findings of this study provided a list of ADAS features, which is incorporated into the questions for this survey study.

The objective of this study was to understand police officers' opinions and needs regarding ADAS in police vehicles and how officer acceptance of ADAS is influenced by different factors. To achieve this objective an online survey was conducted to assess the effects of different factors including trust, perceived usefulness, perceived ease of use, ADAS training, and demographic information of police officers on their intention to use ADAS using the TAM.

2.2. Method

2.2.1. Participants

Seventy-three participants completed the demographic questionnaire, and the results are displayed in Table 2.1.

Table 2.1. Results of demographic survey.

Category	Results
Sex	68 males, 5 females
Age	M = 37.24 yrs., SD = 8.3 yrs.
Number of participants who attended police academy	73
Experience as police officer	M = 11.03 yrs., SD = 7.43 yrs.
Experience serving as a primary patrol officer	M = 8.63 yrs., SD= 6.14 yrs.
Number of participants who received additional training since the police academy (e.g., emergency vehicle operation courses)	63
Level of experience with ADAS (1 being no experience and 5 being an expert)	M = 2.74, SD = 1.19
Frequency of ADAS use	M = 46.11% and SD = 27.19%
Road types drove	Urban, rural, highways, and suburban roads

Note: M: Mean, SD: Standard deviation

2.2.2. Survey

An online survey composed of 19 questions of four different types was distributed among the officers. The question types included: (1) yes/no questions with space for elaboration, (2) Likert scale response questions with ranges of responses between 1 (represents the lowest reported frequency or the lowest possible trust in the technology) and 5, (3) checkbox questions with choices selected based on the findings of our previous literature review (Nasr et al., 2021), and (4) free response questions. The three primary categories included perceived usefulness, perceived ease of use, and trust, with two other questions focusing on training and past behavior. As the final question merely asked for additional suggestions, it was not placed in a category. Table 2.2 outlines the survey questions and the response type.

The questions were based on the ADAS widely available in police vehicles in the U.S. and were designed to understand which features were available in police vehicles, whether they were used by police officers for their work operations, and how useful officers perceived the features. The available ADAS features used in this survey were based on the findings of our literature review (Nast et al., 2021). The ADAS features included were Bluetooth/Uconnect Communication Systems, Rear View Camera, Pre-Collision Assist, Emergency Braking, Lane Keep Assist, Lane Departure Warning, Patented Safety Seat, Adaptive Cruise Control, Hill Start Assist, Hill Descent Control, Reverse Brake Assist, Front Split View Camera, Gunshot Detection System, Automated License Plate Reader, Low-Speed Automated Driving, and Blind Spot Information System. Participants were also asked to rank ADAS features (on their potential usefulness identified in Nasr et al., (2021)) that are currently not widely available in police vehicles. These potential features included: Front Vehicle Detection System, Intersection Collision Avoidance, Evasive Steering Assist, Left Turn Assist, Traffic Sign Detection Algorithm, Post Collision Braking, Traffic Jam Assist, Two Lane Detection, Lane-Ending Detection, Wrong Way Moving Vehicle Detection, Wrong Way Alert, and Autonomous Highway Driving. For descriptions of all ADAS features, please see Nasr et. al., (2021).

Table 2.2. Survey questions and their respective categories.

Question	Response Type	Category
1. What are the most beneficial ADAS features in your police vehicle? Please select all that apply and provide a short explanation for your selection.	Checkbox	Perceived usefulness
2. How often do you use available ADAS features in the police vehicle?	Likert scale	Past Behavior
3. Are there any helpful ADAS features that your personal vehicle has that you would like to have in your police vehicle as well? Which ones?	Free Response	Perceived usefulness
4. Are there any ADAS features in your police vehicle that you do not use at all? If so, please explain.	Yes/No	Perceived usefulness
5. What are your recommendations to improve the current ADAS features in police vehicles?	Free Response	Perceived ease of use
6. If you were the manufacturer of police vehicles, what ADAS features would you add to the vehicle? Why?	Free Response	Perceived usefulness
7. Do you know how to easily turn on and off your ADAS features?	Yes/No	Perceived ease of use
8. Is there any situation in which you would prefer to have your ADAS features turned off? If so, please explain.	Yes/No	Perceived usefulness
9. Would you use ADAS more if their functionality and advantages were clearly explained to you?	Yes/No	ADAS training
10. How do you prefer to receive alerts in your police vehicle? (please select all that apply)	Checkbox	Perceived ease of use
11. Do you think ADAS features can be useful in pursuit situations?	Likert scale	Perceived usefulness
12. How often do you rely on ADAS features while you are performing a secondary task (e.g. using the MCT, cell phone, talking on the radio) as compared to when you are driving without these distractions?	Likert scale	Perceived usefulness

Table 2.2. Survey questions and their respective categories continued.

Question	Response Type	Category
13. Do you think the currently available ADAS features in police vehicles are helpful to improve driving safety and reduce crashes? If yes, please explain how.	Yes/No	Perceived usefulness
14. How much do you trust ADAS features to improve your driving safety?	Likert scale	Trust
15. How much do you trust autonomous vehicles to improve your driving safety in police operations?	Likert scale	Trust
16. To what extent do you think that ADAS features reduce your workload?	Likert scale	Perceived usefulness
17. What are the reasons/barriers that prevent you from using ADAS in police vehicles?	Free Response	Perceived usefulness
18. Do you think that ADAS features improve your attention to the road and the surrounding environment? If yes, please explain how.	Yes/No	Perceived usefulness
19. Do you have any other suggestions to improve ADAS in police vehicles?	Free Response	N/A

A copy of the survey used in this study can be found from https://docs.google.com/forms/d/1w6Tk8tqIFi_RjotGoIXslEe9z6i3w0tw1VWGIK__nco/edit.

2.2.3. Procedure

The survey was administered to participating precincts in Texas via email. Participants were first asked to fill out an online consent form and a demographic survey before completing the actual survey. Responses were collected and organized using Google Forms between September 2nd, 2020 and September 17th, 2020.

2.2.4. Data analysis

2.2.4.1. Research hypotheses

The below hypotheses (H) were tested in this study. The hypotheses were generated based on prior studies using TAM to assess ADAS for civilians.

H1: Trust in ADAS significantly and positively affects officers' behavioral intention to use ADAS (Gefen et al., 2003; Kidd et al., 2017).

H2: Perceived usefulness (PU) has a significant positive impact on behavioral intention (Davis, 1989).

H3: Perceived ease of use (PEU) will have a significant positive impact on behavioral intention (Davis, 1989).

H4: PU mediates the effect of PEU on behavioral intention; however, the mediation is not a complete mediation. In other words, PEU significantly affects behavioral intention, above and beyond PU (Davis, 1989).

H5: Demographic information significantly affects officers' intention to use ADAS. It is expected that younger officers would be more intended to use ADAS as compared to more senior police officers (Lee et al., 2019).

H6: Training the officers on ADAS functionalities and advantages will positively impact behavioral intention towards ADAS use (Biassoni et al., 2016).

H7: Training the officers on ADAS functionalities and advantages will positively affect PEU (Biassoni et al., 2016).

H8: Training the officers on ADAS functionalities and advantages will positively affect PU (Biassoni et al., 2016).

H9: Training the officers on ADAS functionalities and advantages will positively affect their trust in ADAS technologies (Lee and See, 2004).

2.2.4.2.Structural equation modeling

The objective of this study was to reveal the relationships among acceptance of ADAS technologies, trust in ADAS technologies, perceived usefulness, and other related variables. Due to the complex relationships among these latent variables and their measurement error, it was not possible to find the structural relationships using traditional multiple regression or factor analysis. Therefore, a partial least square structural equation modeling (PLS-SEM) methodology was employed, which can be used to study the complex interrelationships among variables. Structural equation models can be graphically shown by path diagrams, and the direction of each arrow represents the causal relation between the two variables connected by the arrow. For this study, the structural equation model was analyzed using SmartPLS 3.2.9 software (Sullivan and Feinn, 2012) (Figure 2.1).

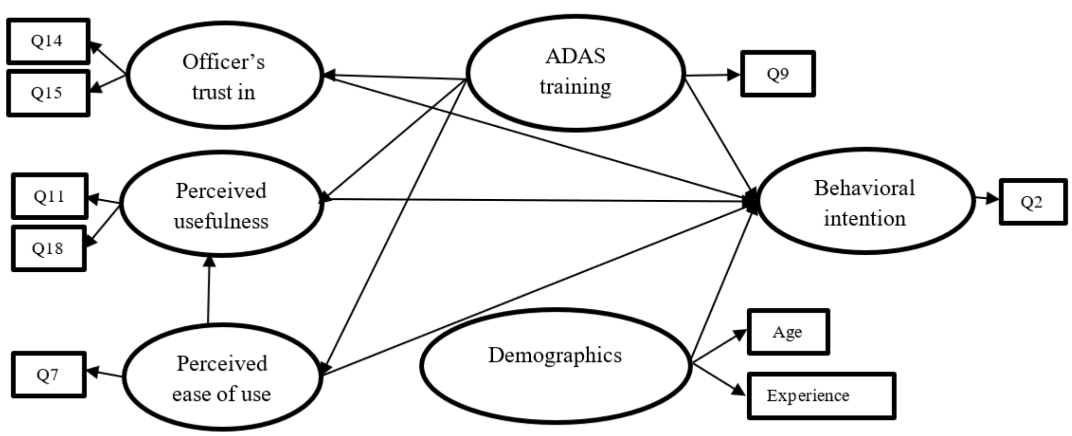

Figure 2.1. Technology acceptance model

2.2.4.3. TAM analysis

According to the recommended two-stage analytical approach proposed by Anderson and Gerbing (1988), the measurement model (validity and reliability of the model) was examined followed by an evaluation of the structural model (testing the hypothesized relationship) (see Hair et al., 2017; Ramayah et al., 2011; 2013; Rahman et al., 2015). During the data analysis process, all of the related questions to each construct were initially included in the model. Then, to make sure that the model meets all of the assumptions (i.e., indicator reliability, internal consistency reliability, convergent reliability, discriminant validity, and model fit), some of the questions were removed and the remaining questions were used in the final model. In addition, a bootstrapping method (5000 resamples) was used to test the significance of the path coefficients and the loadings—estimated relationships in reflective measurement models which determine an item's absolute contribution to its assigned construct (Hair et al., 2017).

2.2.4.4. Model validity and reliability

To ensure that the model used was valid, the indicator reliability, internal consistency reliability, convergent reliability, discriminant validity, and model fit of the model were evaluated. Table 2.3 shows that all of the indicators have individual indicator reliability values that are much larger than the minimum acceptable level of 0.4 (Wong, 2013). Therefore, the model meets the requirements for indicator reliability. Traditionally, “Cronbach’s alpha” was used to estimate internal reliability in social science research. However, some studies proposed the use of “Composite Reliability” instead of Cronbach's alpha to measure the reliability as a more conservative measurement in PLS-SEM (Bagozzi and Yi, 1988; Hair et al., 2012). Based on Table 2.3, all composite reliability values were higher than 0.7, indicating high levels of internal consistency reliability among all six reflective latent variables (Wong, 2013).

Convergent validity was determined by investigating the loadings, average variance extracted (AVE), and the composite reliability of the model (Gholami et al., 2013; Rahman et al., 2015). The loadings were all higher than 0.71, the composite reliabilities were all higher than 0.74, and the AVE of all constructs were also higher than 0.59, which based on the recommendations from Gholami et al. (2013) and Rahman et al. (2015) indicates that the model has convergent validity.

Table 2.3. Summary of model validity results

Latent Variable	Indicators	Loadings	Indicator Reliability (Loadings^2)	Composite Reliability	Average Variance Extracted (AVE)
Officer's trust in ADAS	Q14	.96	.92	.87	.77
	Q15	.79	.62		
Perceived usefulness	Q11	.71	.50	.74	.59
	Q18	.82	.67		
Perceived ease of use	Q7	1.00	1.00	1.00	1.00
ADAS training	Q9	1.00	1.00	1.00	1.00
Demographics	Age	.94	.88	.94	.89
	Experience	.94	.88		
Behavioral intention	Q2	1.00	1.00	1.00	1.00

The square root of AVE of each latent variable was used to establish discriminant validity and was compared with other correlation values as shown in Table 2.4 The square root of AVE of each latent variable was found to be bigger than the other correlations in their column and row, which indicated that the model met the requirements for discriminant validity based on the criteria identified by Fornell and Larcker (1981).

Table 2.4. Fornell-Larcker criterion analysis for checking discriminant validity.

	Officer's trust in ADAS	Perceived usefulness	Perceived ease of use	ADAS training	Demographics	Behavioral intention
Officer's trust in ADAS	.88					
Perceived usefulness	.51	.77				
Perceived ease of use	.03	-.11	1.00			
ADAS training	.22	.41	-.07	1.00		
Demographics	.02	.06	.08	.09	.94	
Behavioral intention	.32	.28	-.05	-.17	.15	1.00

Finally, before proceeding to run the model, model fit was tested by using the standardized root mean square residual (SRMR). The SRMR is defined as the difference between the observed correlation and the model implied correlation matrix in which values equal to or smaller than 0.08 are considered a good fit (Hu and Bentler, 1998). The calculated SRMR of our model was 0.08, which indicates a good model fit.

2.3. Results

2.3.1. Survey

From the participants who completed the demographic questionnaire, the data for seven participants were removed due to failing or choosing not to complete the online survey sent to them. Therefore, survey data analysis was conducted on the data from the remaining 66 participants. A summary of the responses to survey questions are shown in Tables 2.5 and 2.6 and Figures 2.3 and 2.4. For the Likert questions, participants were asked to rate their agreement with a variety of statements, with higher values being more positive responses.

Table 2.5. Descriptive statistics on Likert scale questions.

Question	Mean (Standard Deviation)
2. How often do you use available ADAS features in the police vehicle?	3.05 (1.29)
11. Do you think ADAS features can be useful in pursuit situations?	2.86 (1.35)
12. How often do you rely on ADAS features while you are performing a secondary task (e.g. using the MCT, cell phone, talking on the radio) as compared to when you are driving without these distractions?	2.58 (1.46)
14. How much do you trust ADAS features to improve your driving safety?	2.82 (1.20)
15. How much do you trust autonomous vehicles to improve your driving safety in police operations?	1.94 (1.15)
16. To what extent do you think that ADAS features reduce your workload?	2.15 (1.01)

Table 2.6. Summary of responses to Yes/No questions.

Question	Percentage of "Yes" Responses (%)
4. Are there any ADAS features in your police vehicle that you don't use at all? If so, please explain.	9.09
7. Do you know how to easily turn on and off your ADAS features?	47

Table 2.6. Summary of responses to Yes/No questions continued.

Question	Percentage of "Yes" Responses (%)
8. Is there any situation in which you'd prefer to have your ADAS features turned off? If so, please explain.	37.9
9. Would you use ADAS more if their functionality and advantages were clearly explained to you?	62.8
13. Do you think the currently available ADAS features in police vehicles are helpful to improve driving safety and reduce crashes? If yes, please explain how.	59.1
18. Do you think that ADAS features improve your attention to the road and the surrounding environment? If yes, please explain how.	43.9

Figures 2.3 and 2.4 summarize the results gathered for questions 1 and 10 respectively. Figure 2.3 indicates what features officers believed to be most beneficial to them during their work. These features are available ADAS in the latest police vehicles in the U.S. (e.g., the 2020 Ford Police Interceptor Utility, the 2020 Chevy Tahoe Police Pursuit Vehicle, and the 2020 Dodge Charger Pursuit) but might have not been available in the vehicles of police officers surveyed in this study (which was illustrated in Figure 2.2). Similar to the responses to available ADAS features (Figure 2.2), the responses to question 1 suggested a strong preference of police officers for the rear-view cameras and the Bluetooth communication systems in comparison to all of the other ADAS features. The responses to question 10 indicated officers' preference towards receiving alerts using a combination of visual and auditory modalities as compared to visual or auditory modality only or vibrotactile alerts.

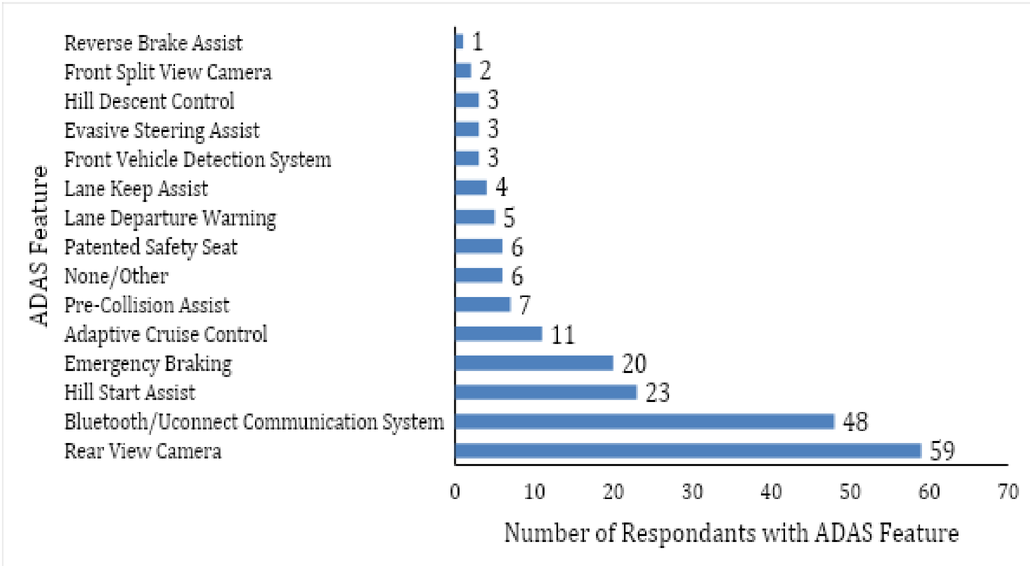

Figure 2.2. Existing ADAS in police vehicles

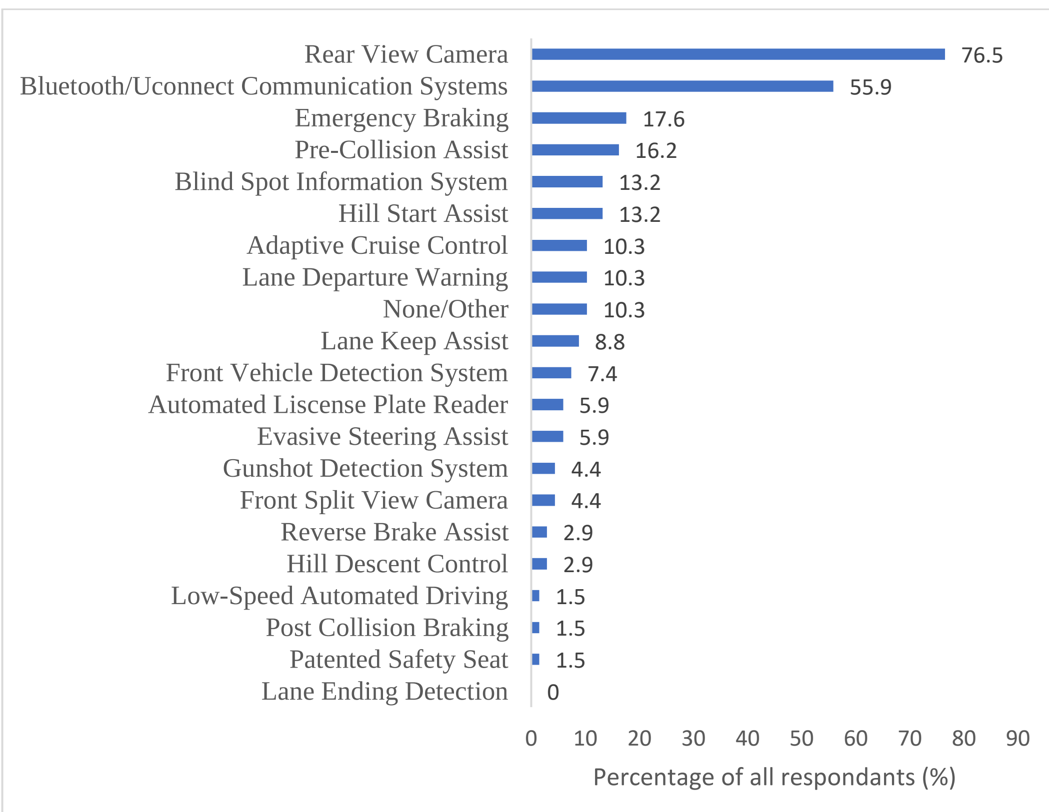

Figure 2.3. Beneficial ADAS features

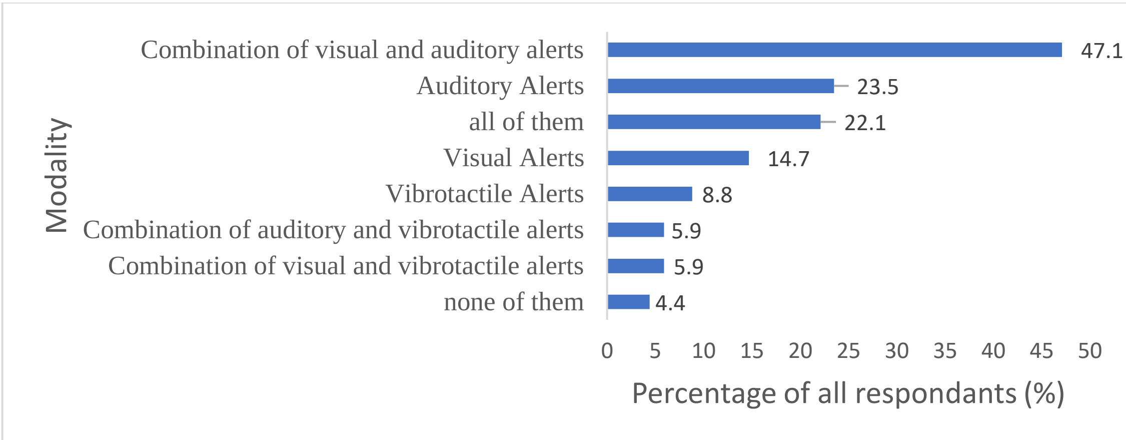

Figure 2.4. Officers' preferred sensory modality to receive alerts

In addition, participants were asked to indicate which ADAS features were available in their police vehicles. The findings of this question are displayed in Figure 2.2. It was found that rear view cameras and Bluetooth communication system were the most common ADAS available in police vehicles, with nearly all survey respondents indicating that they had at least one of these features in their vehicles. Conversely, reverse brake assist and front split view camera were the most uncommon features available.

Participants were also asked to rank potential ADAS features, not currently available in police vehicles in the U.S., based on how useful they thought they could be (1 being the most useful and 12 being the least useful). The most useful potential ADAS features according to the surveyed police officers were as follows (starting with the most potentially useful): Intersection collision avoidance (M = 5.60, SD = 4.06), wrong way alert (M = 5.89, SD = 3.90), front vehicle detection system (M = 5.92, SD = 4.04), evasive steering assist (M = 6.51, SD = 3.69), wrong way moving vehicle (M = 6.59, SD = 3.89), post collision braking (M = 6.67, SD = 3.76), two lane detection (M = 6.59, SD

= 2.92), left turn assist (M = 6.81, SD = 3.61), traffic jam assist (M = 6.85, SD = 3.33), traffic sign detection (M = 7.41, SD = 3.74), lane ending detection (M = 7.44, SD = 3.21), and autonomous highway driving (M = 7.64, SD = 3.86). The results indicated that police officers prioritized ADAS features with regards to avoiding collisions such as intersection collision avoidance over ADAS designed to reduce the mental burdens associated with driving such as traffic sign detection or autonomous highway driving.

2.3.2. Responses to open-ended questions

Several questions were provided in the free response format in order to better retrieve individual opinions of participants. The notable results and implications for these questions are summarized in this section with percentage of participants who reported the comments in the parenthesis.

Question 3: Are there any helpful ADAS features that your personal vehicle has that you would like to have in your police vehicle as well?

The responses for this question were similar to the responses to question 1 of the survey, with blind spot information and cameras compromising the highest percentage of responses of those who responded affirmatively to this question (25.8% response rate for both responses). Following these were collision assistance (22.6%) and cruise control (12.9%), which were not identified as prevalent features available in police vehicles by this survey (Figure 2.2). This may reflect a strong desire of officers to have access to features they do not currently have access to.

Question 5: What are your recommendations to improve the current ADAS features in police vehicles?

Improvements to ADAS adaptability and usability were the most common requests from police officers to enhance existing ADAS features in police vehicles, included in 17.6% of responses. Specific examples officers cited include being able to enable and disable features such as front vehicle detection and lane assist easily, and clearly explaining how the ADAS features work so they can be properly utilized. About 7% of officers requested the removal of ADAS without citing reasons. These responses justified the decision to categorize this question within the perceived ease of use category, as many officers expressed interest in improvements to existing ADAS features as opposed to suggesting new features entirely.

Question 6: If you were the manufacturer of police vehicles, what ADAS features would you add to the vehicle? Why?

Similar to question 3, cameras were cited as critical to police officers when questioned on what they would add to police vehicles, comprising 19.1% of responses. Crash avoidance systems such as collision and braking assistance were also cited often (16.1% of responses). It is noteworthy that police officers favored ADAS that are designed to prevent crashes (e.g. rear-view cameras, emergency braking systems, and blind spot monitoring systems) over systems that can improve their driver control responsibilities, even in free response questions. What this might indicate is that police officers prioritize the ability of ADAS to assist officers in dangerous/accident situations above any other ADAS feature quality when evaluating ADAS.

Question 17: What are the reasons/barriers that prevent you from using ADAS in police vehicles?

Lack of access was the primary reason cited for being unable to use ADAS in police vehicles, comprising 35.3% of responses. Some specific reasons mentioned included lack of department funding or unwillingness to purchase additional features for police vehicles. More importantly, perceptions of reliability and effectiveness filled the next two spots at 14.7% and 13.2% of responses respectively, indicating that a fundamental shift in the philosophy of manufacturers towards proper explanation and accommodation for police officers could potentially increase ADAS use among police officers and improve safety.

Question 19: Do you have any other suggestions to improve ADAS in police vehicles?

Standardization of ADAS features and adaptability were cited as the most desired changes, comprising 27.8% and 10.7% of responses of those who responded affirmatively to this question respectively, though responses were more varied as compared to other questions. Officers recommended that ADAS features should be compatible with existing police vehicles and technologies such as MCTs, and should be quickly activated, deactivated, or changed its settings based on the needs of the situation and police officers. Officers expressed discontent with the incompatibility between features unique to police vehicles, such as the MCT, and the ADAS available in their vehicles. This issue creates unnecessary barriers for police officers using ADAS while driving as they have to interact with both MCT interface and separate user interfaces for those ADAS features. This highlights a disparity between civilian drivers and police officers that creates a need for a unique approach to manufacturing and researching ADAS specifically designed for police vehicles.

2.3.3. Technology acceptance model

As shown in Figure 2.5, officer's trust in technology ($\beta = 0.26$, $t = 2.27$, $p = 0.01$, $f^2 = 0.07$) and ADAS training ($\beta = -0.35$, $t = 3.54$, $p < 0.01$, $f^2 = 0.14$) affected officer's behavioral intention to use ADAS, explaining 25% of the variance in their behavioral intention. It is important to note that the negative relationship between ADAS training and behavioral intention was due to how Q9 was structured (See Table 2.2). ADAS training ($\beta = 0.4$, $t = 2.69$, $p < 0.01$, $f^2 = 0.2$) was also found to be a significant predictor of driver's perceived usefulness of ADAS features.

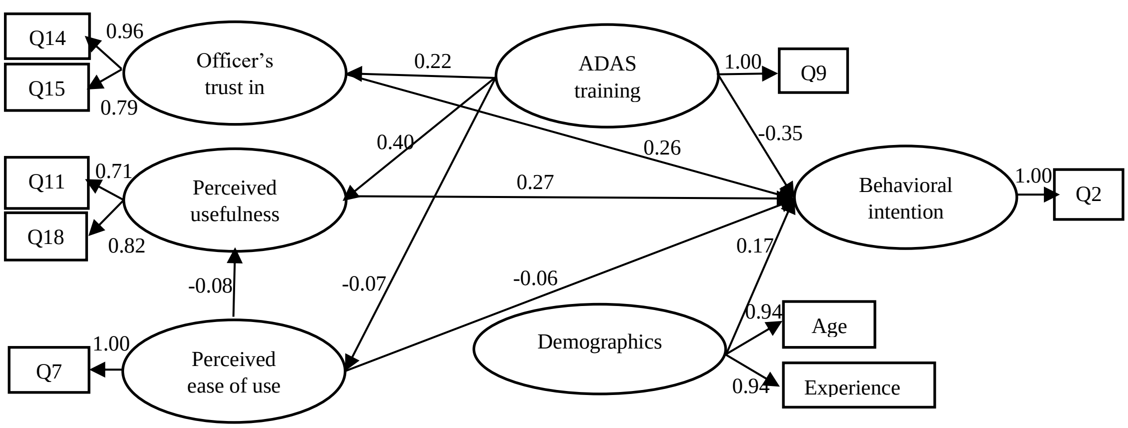

Figure 2.5. Technology acceptance model results

2.4. Discussion

2.4.1. Survey results implications

A majority of officers (91.2%) indicated that there are several ADAS in their police vehicles that they never use. Considering question 17 where officers indicated lack of departmental budget as a primary barrier to implementation of ADAS in police vehicles, it is reasonable to conclude that the ADAS features that are implemented in police vehicles should be reconsidered. Coupled with the 58.5% of officers that indicated that ADAS could be at least somewhat useful in pursuit situations and the 57.4% of surveyed officers that believed ADAS are helpful for improving driving safety and reducing crashes, a clear disconnect between officer ADAS use and their belief in its effectiveness is visible. In order to resolve this discrepancy, useful ADAS have to be identified and standardized to be used in police vehicles. As multiple officers indicated in question 19, manufacturers have to be able to consider what features are useful for police vehicles specifically instead of treating them the same as civilian vehicles.

As indicated in responses to question 1, Bluetooth, rearview cameras, and emergency braking were the most beneficial ADAS features in police vehicles, yet over 60% of respondents rated their belief that ADAS reduces their workload as 2 or less on a scale of 5. Furthermore, roughly 40% of officers indicated that they almost never use ADAS while they are performing a secondary task. When coupled with the 67.6% of respondents who indicated that they would use ADAS more if the functionality and advantages were more clearly explained to them, it can be concluded that the education of officers in ADAS use is either ineffective or not sufficient. The easiest way to surmount this hurdle would be to design ADAS such that they are intuitive to use and therefore, they reduce the need for ADAS training and confusion on the part of officers. In doing so, officers would make better use of the features available to them and a clearer picture of which ADAS features are truly the most helpful for police officers would appear. Beyond this, 47.1% of officers indicated that they prefer a combination of visual and auditory alerts over single visual or auditory alerts and vibrotactile alerts for their police vehicles. Therefore, to improve ADAS access, manufacturers should take advantage of these multi-modal alerts.

2.4.2. Technology acceptance model implications

Table 2.7 summarizes the findings of the TAM. These findings are discussed in detail in this section.

Table 2.7. Summary of the results of the Technology Acceptance Model.

Hypothesis	Result
H1: Trust in ADAS significantly and positively affects officers' behavioral intention to use ADAS.	Supported
H2: Perceived usefulness (PU) has a significant positive impact on behavioral intention.	Rejected
H3: Perceived ease of use (PEU) will have a significant positive impact on behavioral intention.	Rejected
H4: PU mediates the effect of PEU on behavioral intention; however, the mediation is not a complete mediation. In other words, PEU significantly affects behavioral intention, above and beyond PU.	Rejected
H5: Demographic information significantly affects officers' intention to use ADAS. It is expected that younger officers would be more intended to use ADAS as compared to more senior police officers.	Rejected
H6: Training the officers on ADAS functionalities and advantages will positively impact behavioral intention towards ADAS use.	Supported
H7: Training the officers on ADAS functionalities and advantages will positively affect PEU.	Rejected

Table 2.7. Summary of the results of the Technology Acceptance Mode continued.

Hypothesis	Result
H8: Training the officers on ADAS functionalities and advantages will positively affect PU.	Supported
H9: Training the officers on ADAS functionalities and advantages will positively affect their trust in ADAS technologies.	Rejected

Similar to the findings of Gefen et al. (2003) and Kidd et al. (2017), driver trust was found to significantly and positively affect driver's intention to use ADAS (supporting H1). Trust identifies the way people interact with technologies (Hoff and Bashir, 2015) and can evolve over time. As more and more ADAS technologies are added into vehicles, more people will make use of them and in turn discover the benefits of ADAS in exchange for minimal effort while driving (Dai et al., 2020). Furthermore, long term education and strategies are needed to familiarize drivers with ADAS technologies and to increase the acceptance and trust in them. Since trust is based on drivers being able to effectively use and rely on ADAS features, it is important to find an effective way to train police officers on ADAS functionalities and effectiveness. By having officers use ADAS in situations similar to real world patrols, they will be more likely to implement and use them as they become more experienced with the technology.

Police officers are involved in multitasking situations while driving, such as communicating with dispatch officers and using their MCTs, making the diversion of attention to any sort of ADAS feature more difficult than for the average civilian driver. To increase clarity and facilitate the transmission of information between ADAS and driver, ADAS warnings regarding changes in system status should be provided in an appropriate time and manner while in use. In doing this, however, driver annoyance associated with false alarms must be minimized to avoid undermining driver trust through false positives (Barchéus, 2006). Previous studies indicated that operator trust in ADAS is strongly related to reliance on automated systems and patterns of system usage (Parasuraman and Riley, 1997). This is not to say that complete reliance on ADAS features is conducive to effective driver performance, rather that ADAS technologies that are able to seamlessly integrate themselves with driver expectations of their functionalities are more likely to create high trust in drivers (Weiss et al., 2018). Therefore, research and manufacturing in the future should concentrate on lining up the capabilities of what ADAS features can do with what police officers expect in order to build trust and best encourage ADAS use.

Hypotheses 2 (H2) and 3 (H3) stated that perceived usefulness and perceived ease of use of ADAS can impact intention to use ADAS. These hypotheses and consequently H4 were not supported by the data as there was no significant effect of perceived usefulness or ease of use on behavioral intention. One possible explanation for this observation is a lack of exposure to the ADAS features that would be the most beneficial to police officers. According to the demographic survey, many officers do not have a wide range of ADAS features readily available in their vehicles (see Figure 2.2), meaning that perceptions of ADAS as being easy to use or even useful may be biased by the lack of ADAS features police officers have access to.

Hypothesis 5 (H5) was also not supported by the data. No significant effect of age or experience on driver behavioral intention to use ADAS technologies was observed in our analysis. This might be due to the limited age range of our participants. Most of the officers who participated in our study were between 30 and 40 years of age. Therefore, we did not see any significant effect of age on their intention to use ADAS. In addition, drivers' gender was not included in the analysis as only five female officers responded to our survey.

The findings supported hypothesis 6 (H6) in that training the officers on ADAS functionalities and advantages would positively impact behavioral intention towards ADAS use. Officers who indicated more interest in learning about ADAS features (i.e., they currently do not have sufficient knowledge of ADAS), exhibited less intention to use the ADAS features. What this means is that officers educated in ADAS are more likely to indicate high intention to use ADAS than officers that are not educated in ADAS use. Thus, there is a need to provide officers with more training on ADAS features to increase their intention to use ADAS. Various training approaches such as paper-based manuals, multi-media software tools, video-based training, and simulator-based training can be employed to teach officers. Portouli et al. (2008) found that multi-media software and driving simulator training led to better performance with ADAS technologies as compared to paper-based training methods. However, driving simulator-based training can be costly depending on the level of fidelity and might not be as accessible as other training approaches for training police officers. When driving simulation-based training is not available, multi-media software training tools can be used as a substitute for training officers in ADAS technology use.

Hypothesis 7 (H7) was not supported by the data as training on ADAS functionalities did not significantly impact perceived ease of use. It is important to note that these findings are based on the opinions of officers, not their actual performance with the ADAS features. In order to determine if ease of use is significantly affected by ADAS training, further simulation or observation studies would be necessary. Otherwise, it is difficult to determine if the lack of a relationship between training and perceived ease of use is a result of the training, design of the ADAS feature, or some other cause. That in mind, the data did support Hypothesis 8 (H8), which indicated that ADAS training can have a positive impact on perceived usefulness. What is highlighted here is the important distinction between perceived ease of use and perceived usefulness, that these two concepts are not perfectly correlated to each other. The results imply that, while the information officers have on ADAS features may be initially limited by the lack of features available or lack of desire to use the features, training has the ability to improve their opinion on the usefulness of ADAS features as a whole. Future research should therefore focus on determining what aspects of both the ADAS training and the ADAS features themselves have the highest impact on officer’s opinions on the usefulness of ADAS features as a whole. Through this, training protocols and manufacturing can be adapted to help overcome the critical knowledge barrier to increase ADAS use by police officers.

Hypothesis 9 (H9) stated that training positively affects driver trust in ADAS, which was not supported by the data. ADAS training in our study included a subjective question of their interest in learning and receiving training on ADAS features. Trust can be built throughout experience and time, and subjective inheritress of question 9 may cause individual biases. Since officers were not provided with actual training to learn about ADAS features, their responses might be biased when it comes to driver trust in technology and should be interpreted with caution. In fact, operator training has been found to be an important part of successful use of ADAS (Parasuraman & Riley, 1997), and training was found to be a critical missing component in the deployment of today's ADAS. For example, Reimer et al. (2010) studied the effect of training on a semi-automated parallel parking system. Without training, participants reported that the system was not overly likely to reduce their stress when parking or improve their performance. However, after being fully trained on the operation and features of the technology, their performance and stress level (measured by physiological measures) while parking were improved. They concluded that participants who became familiar with the technology through more exposure, reported more positive expectations and acceptance of how the technology could reduce their stress. In line with Reimer et al. (2010), Biassoni et al. (2016) found that increasing the quantity and quality of information on technology features provided to the driver can substantially change the initial acceptability of the device and driver trust in technology. Therefore, it can be concluded that increasing the exposure time and information to participants can positively affect their attitude and acceptance toward using ADAS.

2.4.3. Limitations

This study had some limitations. First, the participants were exclusively recruited from police departments in the state of Texas. As a result, the findings may not be directly applicable to agencies utilizing different types of police vehicles or operating in other states where vehicle designs and technologies might vary. It is important to acknowledge that the specific characteristics and features of police vehicles can differ across jurisdictions, potentially influencing the results and generalizability of this study. Second, many of the surveyed participants drove police vehicles that had a limited number of available ADAS. This could have led to biased results favoring the few ADAS features currently in the vehicles of the police officers surveyed due to lack of experience with all surveyed ADAS features. The question used to measure behavioral intention was a question that measured past behavior. While the use of past behavior as a predictor of future behavior has been validated in prior studies (Amoako-Gyampah, 2007; Jackson, 1997), it is not a direct measure of behavioral intention. Therefore, future studies need to validate the findings of this study with more direct measures of behavioral intention. Finally, the distribution of question types among the category of questions was unbalanced. Although having a balanced distribution of question types per each category is not required for the validation of the TAM analyses (Igbaria, 1995), it is possible that increasing or changing the category for some of the questions could have affected the results of the study. This issue needs to be further investigated in future studies.

2.4.4. Future research and recommendations

In order to encourage productive future research, several guidelines are presented here based on the results of this study. Though many general heuristics for vehicle ADAS design exist (Stevens, 2002; Inakagi, 2011; Hansen, 2012) and our recommendations are by nature directly and indirectly tied to them, there are several key differences that separate police vehicles from civilian drivers and necessitate this more specific set of guidelines for future research and manufacturing. These differences are elaborated on here.

Many guidelines that currently exist for designing civilian ADAS emphasize the importance of reducing visual and auditory distractions in vehicles (Focus-telematics, 2006), which is not possible for police officers who have to complete multiple secondary tasks while driving to effectively carry out their job duties. As the officer is already going to be distracted by these secondary tasks, ADAS features for police vehicles have to be able to be quickly and effectively understood in a way that is intrusive enough to get the officer's attention when necessary so the officer can more safely accomplish secondary tasks that pull their attention away from the road. Another important distinction between current guidelines and what is presented here is the lower emphasis on training and training guidelines. As ADAS technology becomes more complicated and the issue of trust in ADAS continues to raise problems with its use, literature focused on describing how ADAS training should be carried out has grown (Manser, 2019). For police officers, however, the study found that the mental hurdles associated with extensive training can actually prevent officers from making full use of their ADAS features given how much they have to account for in their vehicles already. Thus, our guidelines put less emphasis on elaborating on extensive ADAS training or developing ADAS with more features and capabilities and more on intuitive, streamlined features that, though they might not be able to perform as many tasks as more complicated ADAS vehicles, will overall be more effective in encouraging use by police officers.

This is not to say that the presented guidelines go directly against all pre-existing heuristics for ADAS vehicle design. It has been shown through literature on modern vehicle design emphasizing the importance of designing safety features to account for the varying driving habits of users that there is a need for more specification in guidelines for drivers whose driving habits differ from the average civilian (Happian-Smith, 2001). Police officers, by the nature of their profession, experience a higher workload while driving as compared to civilian drivers, meaning heuristics that may be established for design for civilian drivers will at least need to be justified for use for design of police officer vehicles.

Workload can be viewed as a direct source of stress from a job, caused by either the frequency of a task or the nature of the task itself (Stotland & Pendleton, 1989). Workload is a comprehensive organizational variable that can have many consequences on workers. Unfortunately, the workload of police officers has been found to be beyond the acceptable limits compared to other jobs (Sen, 2015). In addition, research on policing and stress suggests that police work is very stressful (Anderson et al., 2002). Sen (2015) conducted a survey study to evaluate police officers' workload. Results from

336 participants suggested that a majority of police officers have above normal workload perception (including heavy and unmanageable workload).

Due to the limitations of mental resources, if a task demands exceed resource capacity, information overload and degradations in task performance will occur, especially when the tasks compete for the same pool of attention (Wickens, 2008). Police officers are usually required to multitask when driving which leads to a higher workload as compared to civilian drivers who are not required to do non-driving related tasks. In addition, temporal demands placed on the officers due to the need for real-time information access and complexity of driving situations (e.g., driving in high speed and in pursuit conditions) can increase their workload as compared to civilian drivers (Zahabi & Kaber, 2018).

To account for these differences between police officers and the general population, it is necessary to better advance the development of ADAS features to improve officer safety. Therefore, the following list of guidelines has been determined in order to guide future research and to improve ADAS in the next generation of police vehicles. These guidelines are meant for both researchers and manufacturers of ADAS features to consider when undertaking future development of ADAS, in particular for police vehicles.

Guideline 1: Emphasize clarity above everything else.

One of the largest barriers to ADAS usage for police officers was identified as a lack of understanding of the ADAS features available. About 68% of respondents affirmed that they would make greater use of ADAS if the functionality and advantages were more clearly explained. Since TAM showed that ADAS training significantly impacts perceived usefulness and officers' intention to use these features, improving officers' knowledge of ADAS can potentially increase ADAS acceptance among police officers.

Guideline 2: Improve ADAS accessibility and usability

About 38% of police officers stated that there were situations where they preferred to have their ADAS features disabled. However, over half of the respondents identified that they were unable to easily turn on or off their ADAS features. Accessibility and usability, desired qualities according to the free response results, should be emphasized in the design of ADAS to account for individual differences and preferences of police officers when using ADAS features.

Guideline 3: Provide adaptive ADAS

Police driving conditions including pursuit and emergency operations are different from the situations that civilian drivers are involved in. Therefore, ADAS features for police vehicles should be easily adaptable to these situations or powered off effectively otherwise. Pursuits and other similar situations were the top reasons cited by police officers with regard to situations where they preferred to have their ADAS features off. Thus, when designing or researching ADAS features, adaptability to the wide variability of driving scenarios police officers face is paramount.

Guideline 4: Investigate ways to integrate ADAS into existing police vehicle technology.

Police officers already have multiple unique features (e.g., MCT, radio) in their vehicles compared to civilian drivers. These features, while necessary for police officers to perform their duties, significantly increase officers' mental workload and distraction while driving (Shupsky et al., 2020; Zahabi & Kaber, 2018). Officers indicated that ADAS should be compatible with existing police in-vehicle technologies and should be easily activated or adjusted based on individual preferences, needs, and driving situations. This highlights a need for a unique approach to design and manufacture ADAS for police vehicles. Furthermore, research should be conducted on whether integrating ADAS into police vehicle technology would encourage higher ADAS use among police officers.

Guideline 5: Focusing on perfecting a few features is better than having many less elaborate features.

Police officers experience higher levels of workload than civilian drivers. The survey indicated the lack of understanding regarding ADAS as one of the primary barriers towards using ADAS features for police officers. To combat this, researchers and manufacturers should focus on ADAS features, which target the factors specified above when designing for police vehicles, with future research validating the directions chosen for designing such features. Furthermore, building the trust that compromises the main significant contributor towards officers' intention to use ADAS requires that officers understand the nature of the features they are using. As officers already have high mental workload associated with their jobs, a few features that help them perform their duties effectively would be much easier to understand and trust than a multitude of complex features.

Guideline 6: Design to reduce the need for extensive ADAS training

The TAM results indicated that ADAS training has a significant effect on officer intention to use ADAS and perceived usefulness of ADAS. Useful as ADAS features are, the prospect of needing to undergo training to fully understand and utilize these features can be daunting to police officers already burdened with high mental workload and stressful jobs. To account for this while not sacrificing the trust gained from understanding how ADAS features work, future research should investigate ADAS features that require minimal training to understand, and manufacturers should endeavor to design intuitive ADAS that perform their duties with as little required attention or input from the driver as possible. This includes the activation and deactivation of these systems, in accordance with guideline 2. Furthermore, the training should be delivered in the form of multi-media software tools or driver simulators when possible and should be simple to overcome the mental hurdles police officers face when taking on additional tasks while driving.

3. DRIVING SIMULATION STUDY

3.1. Introduction

Crash reports from various states in the U.S. have revealed high numbers of emergency vehicle crashes, especially in law enforcement situations. MVCs are among the leading causes of LEO deaths and injuries (Tiesman & Heick, 2014). From 2011 to 2015, police vehicle crashes accounted for almost one-third of all law enforcement fatal work injuries (BLS, 2016). Although overall law enforcement fatalities in pursuit situations have decreased moderately from over 160 per year in 1980 to under 120 per year in the late 2000s, deaths caused by motor vehicle crashes have steadily increased (Lambert, 2016).

ADAS are vehicle control systems that improve driving comfort and traffic safety by using vehicle sensors (e.g., radar, laser) helping the driver identify and react to potentially hazardous traffic situations (Gietelink et al., 2006). ADAS are expected to mitigate road fatalities and reduce the number of road accidents and injuries. Some ADAS such as FCW systems and low-speed autonomous emergency braking (AEB) can reduce property damage and liability claims (Lund, 2013). Wu et al. (2018b) found that driving with FCW resulted in quicker reaction times (shorter throttle release and brake time) and larger response intensity (larger maximum brake pedal force and larger maximum lane deviation) as compared to driving without FCW. In addition, FCW was found to reduce the number and severity of crashes (Cicchino, 2018). In another study, it was found that a combination of FCW, pre-crash brake assist (PBA), and autonomous pre-crash braking (PB) could reduce the change in velocity during the crash by 34%, decrease number of passenger fatalities or injuries by 50%, and prevent 7.7% of collisions (Kusano & Gabler, 2011). Accident involvement rates in lane-change crashes were also found to be 14% lower among vehicles with BSM as compared to those without (Cicchino, 2018).

Though previous work has emphasized the potential of ADAS for reducing accidents in civilian drivers (Davidse, 2006), very few studies focused on potential benefits of ADAS use in police vehicles. Our previous literature review and survey studies were the only investigations in this domain (Nasr et al., 2021; Wozniak et al., 2021). Although survey results provide a useful overview of officers' opinion regarding the ADAS technologies, they are subjective and may suffer from biases. Therefore, there is a need for a driving simulation study to observe officers' performance and investigate the effects of ADAS technologies on LEOs' performance and workload by collecting objective driving behavior data.

Results from the survey study in chapter 2 suggested that although officers preferred to have ADAS features such as pre-collision assist, emergency braking, and BSM in their vehicle, few of police officers have these features implemented in their vehicle. This driving simulation study aims to assess the effectiveness of BSM, FCW, and AEB on police officers' workload and performance. The following sections provide an introduction on driver workload and performance measures when driving with ADAS technologies based on the literature.

3.1.1. Driver performance measures

Driver performance refers to "*the human perceptual and physical capabilities and limitations that affect safe driving*" (McLaughlin et al., 2009). Driver performance metrics are usually defined in terms of speed and braking behavior, steering behavior, time to collision (TTC), glance behavior, driving-related task performance, headway time, lane keeping behavior, lateral acceleration, and number of crashes (McLaughlin et al., 2009). However, different aspects of driving performance can be measured depending on the goal and area of the study. Table 3.1. lists the most frequently used driving performance measurements in previous studies focused on ADAS technologies.

Table 3.1. Driving performance measurements.

ADAS feature	Measurement (unit)	Description	References
BSM	Time to change lane (s)	The duration from when the lead vehicle starts to brake until the subject vehicle fully transitions to the adjacent lane.	Chun et al. (2013)
	Collision prevention rate (CPR) (%)	The number of successful collision avoidances divided by the total number of blind spot collision events.	Chun et al. (2013)
FCW (+AEB)	Collisions (ct.)	Number of collisions	Lindgren et al. (2009); McGehee et al. (2002); Muhrer et al. (2012); Portouli and Papakostopoulos (2014)
	Minimum TTC (s)	Minimum of the time remaining prior to a collision if the path and speed of the subject and lead vehicle are maintained as a constant.	Koustanaï et al. (2012); Lindgren et al. (2009); McGehee et al. (2002); Muhrer et al. (2012)
	Standard deviation of lateral position (m)	Standard deviation of lane position from center of the lane.	Chang et al. (2009); Lindgren et al. (2009); Portouli and Papakostopoulos (2014)

Table 3.1. Driving performance measurements continued.

ADAS feature	Measurement (unit)	Description	References
	Maximum longitudinal deceleration (m/s^2)	The rate of change in velocity in the direction of the vehicle's longitudinal, or X axis.	Koustanaï et al. (2012); Muhrer et al. (2012); Widman et al. (1998)
	Brake reaction time (s)	The time from the braking event of the lead car to the start of the braking of the driver.	Chang et al. (2009); Koustanaï et al. (2012); McGehee et al. (2002); Muhrer et al. (2012); Portouli and Papakostopoulos (2014)
	Time headway (s)	The elapsed time between the front of the lead vehicle passing a point on the roadway and the front of the following vehicle passing the same point.	Koustanaï et al. (2012); Muhrer et al. (2012); Portouli and Papakostopoulos (2014); Widman et al. (1998)
	Maximum lateral acceleration (m/s^2)	The component of the linear acceleration of the vehicle along its lateral, or Y axis.	Fleming et al. (2019); McGehee et al. (2002); Portouli and Papakostopoulos (2014); Widman et al. (1998)
	Collision speed (m/s)	If the subject vehicle collides with the lead vehicle, the collision speed is recorded to assess the severity of each crash.	McGehee et al. (2002)
	Maximum brake input pressure (N)	Maximum brake pressure provides a good estimate of the force a subject has exerted on the brake pedal.	McGehee et al. (2002)
	Maximum steering input (degree)	Measures the greatest steering wheel deviation to either the left or the right.	McGehee et al. (2002)

3.1.2. Driver workload measures

Workload is defined as the amount of information processing capacity or mental resources used for performing a specific task (Hoeger et al., 2008). There are various methods to measure driver workload such as using physiological measurements (e.g., Percentage change in pupil size (PCPS)), subjective measurements (e.g., NASA-TLX, driving activity load index (DALI)), primary-task performance measurement, and secondary task performance measurements (e.g., NDRT accuracy or completion time) (De Waard & Brookhuis, 1996). Table 3.2 demonstrates some examples of workload measurements in driving domain.

Table 3.2. Workload measurements

Measurement type	Response	Reference
Subjective measures	NASA-TLX score	Chen et al. (2019); Wu et al. (2019); Yoon and Ji (2019)
	Driving load activity index (DALI) score	Lahmer et al. (2018); Walch et al. (2018); Zahabi et al. (2021b)
	Rating scale mental effort (RSME)	Lank et al. (2011); Md. Yusof et al. (2017); Schermers et al. (2005)
Physiological measures	Average heart rate	Gable et al. (2015); Li et al. (2004); WAARD et al. (1995)
	Root mean square of successive differences between normal heartbeats (RMSSD)	Baek et al. (2015); Esco and Flatt (2014); Jung et al. (2014); Salahuddin et al. (2007)
	EEG variation rate	Kim et al. (2014); Kim et al. (2013); Zhao et al. (2012)
	Blink rate	Shahini et al. (2021) Recarte et al. (2008b); Yahoodik et al. (2020)
	Percentage change in pupil size (PCPS)	Gable et al. (2015); Zahabi et al. (2021a); Zahabi et al. (2021b)
Secondary-task performance measures	Secondary task accuracy	Shahini et al. (2021)
	Secondary task completion time	Shahini et al. (2021)

3.1.3. Influential factors on officers’ performance and workload

3.1.3.1. Effects of non-driving related tasks

Previous studies found that drivers are inclined to engage in an NDRT when they do not have to monitor the driving environment (Carsten et al., 2012; Dogan et al., 2017). Automated driving is associated with passive fatigue and underload, which is characterized by loss of awareness and low workload (Neubauer et al., 2012). Therefore, engaging in an NDRT may be a self-regulatory approach to counteract the effect of underload. On the other hand, some studies found that engaging in a NDRT may not impact motor readiness following a takeover request. However, it can have a detrimental effect on the quality of the takeover performance. For example, Zeeb et al. (2016) did not find any effects of the type of NDRT (sending an email, reading news, and watching a video clip) on motor readiness (i.e. time to put hands on the steering wheel). However, they observed that lateral control of the vehicle was impaired among the drivers who were reading news and watching a video clip. In line with Zeeb et al. (2016), Merat et al. (2012) found that a verbal quiz task did not influence time to start lane change maneuver, but it influenced speed control. A ride-along study by Zahabi et al. (2021b) revealed that officers perceived the MCT to significantly increase their visual, cognitive, and physical demands compared to other in-vehicle technologies such as radio and cellphone.

Therefore, there is a need to investigate the effects of NDRT on police officers' performance and workload who typically drive under high speed and high workload driving conditions and may use ADAS technologies.

3.1.3.2. Effects of pursuit driving condition

Police driving conditions can be classified into three driving groups, including standard patrol (i.e., regular driving in which all roadway rules are followed), emergency response, and vehicle pursuit. In addition, officers may need to engage in NDRTs and driver at high speed in pursuit conditions. Distracted driving in high speed may increase the probability of the crashes with serious injuries (Chu, 2016). While driving in emergency and pursuit conditions might represent a small portion of police vehicle driving time, the probability and severity of crashes in these situations are much higher than the normal driving condition (Hutson et al., 2007; Rivara & Mack, 2004). A driving simulation study by Zahabi et al. (2021a) found that driving in pursuit condition can degrade driving performance (as measured by speed deviation and lane deviation) and increase officers' workload (as measured by DALI score and PCPS).

3.1.4. Models of driver behavior

3.1.4.1. Braking model

The transition of driving state from normal driving to near-crash conditions is of great significance when designing a FCW hazard assessment algorithm. Markkula et al. (2016) conducted a comprehensive literature review of driver behavior models predicting near-collision braking behavior and found that while normal driving behavior is significantly different from near-collision behavior, normal driver behavior models have been employed to understand near-collision behavior. Markkula et al. (2016) categorized the braking models into two groups as non-satisficing models (i.e., models where the driver starts to brake at the instant when a collision course is established) and models that present satisficing behavior, where the driver starts to brake based on the driver's safety margins and time to collision.

In the category of non-satisficing models, the Gazis, Herman, and Rothery (GHR) model (Markkula et al., 2016) was developed to predict car-following behavior where the driver's braking behavior depends on the following vehicle's velocity, headway distance, and relative velocity (Gazis et al., 1961). The GHR model is nonlinear and contains many parameters. Prior research has been focused on finding the right parameters for the model to improve realism and even simplify the model (Brackstone & McDonald, 1999; Gazis et al., 1961; Yang & Peng, 2010). For example, Lee (1966) made an assumption that driver responds to the relative speed of the following vehicle over a period of time and not instantly. Therefore, the author introduced a memory function into the linear GHR model to store the information related to the relative speed of the vehicles during car following maneuver. Prior studies found that most passenger cars have a greater deceleration than acceleration capacity (Siuhi & Kaseko, 2010; Subramanian, 1996). Ahmed (1999) adjusted the GHR model to contain this acceleration/deceleration asymmetry in the model. Herman (1959) assumed that drivers follow more than one lead vehicle and consider other vehicles ahead and extended the linear GHR model by adding sensitivity terms for up to m vehicles ahead. The models assumed that the drivers are aware of their exact speed, their headway distance, and other environmental factors. Clearly, this assumption is not realistic. However, a fuzzy-logic model by Kikuchi and Chakroborty (1992) acknowledges the imperfection of a driver's prediction ability by dividing their perception into a number of overlapping fuzzy sets using predefined fuzzy-logics. Another model class which has been widely employed for exploring forward collision warning systems is the delayed constant deceleration model, defined by Markkula et al. (2016) as "starting at a (reaction) time T after a stimulus S, the driver applies a constant deceleration D." This definition approximates the behavior of the GHR model in situations where the following vehicle decelerates. The stimuli included sudden appearance of an unexpected obstacle, first glance back towards the road after a lead vehicle has begun deceleration, and the establishment of an initial collision. Considering these stimuli, the resulting models from GHR would be non-satisficing since they do not account for the driver's safety margins while representing the start of braking (Karunagaran, 2018).

In the category of satisficing models, Lee (1976) found that TTC can be estimated using a visual variable related to the optic flow field of the driver, and proposed that drivers start to brake once this visual variable crosses a threshold. Another popular satisficing model is the car-following model by Gipps (1981) that calculates a safe speed with respect to the preceding vehicle by employing limits on a driver's braking rate. Based on Gipps model, drivers adapt their speed to smoothly reach the desired speed or to safely proceed behind their leader (Gipps, 1981). Kiefer et al. (2006) suggested that the driver starts to brake once the inverse time to collision (TTC^{-1}) exceeds a speed dependent threshold. Markkula et al. (2016) conducted several simulations with the Gipps model and found that the TTC^{-1} values when the driver starts to brake follows a similar trend to the speed dependent thresholds of Kiefer et al. (2016) (Markkula et al., 2012). Markkula et al. (2012) suggested a model that could explain both routine and near-crash driving behaviors. The features of this model are listed below:

• It assumes that driving task contains a series of discrete adjustments rather than a continuous closed loop control task.

• The timing of these adjustments depends on the accumulation of evidence such as TTC^{-1}.

• The amplitude of the adjustments is based on the value of the evidence and the predicted effect of adjustments on the evidence (Markkula, 2014).

Markkula (2014) proposed an accumulator model that used a visual estimate of the TTC^{-1} that was able to effectively predict the brake reaction time using the driving database of Kiefer et al. (2006), when the lead vehicle was moving.

τ^{-1} is a visual-based estimate of inverse TTC (Lee, 1976) and is calculated as follows:

$$\boldsymbol{\tau^{-1} = \frac{\dot{\theta}}{\theta}} \qquad \text{Equation 3.1}$$

θ is visual angle in equation 3.1 and is defined as the projected angle of the visual object (e.g., lead vehicle) on driver's retina, and $\dot{\theta}$ is defined as the visual angle expansion rate. Visual angle and expansion rate can be calculated using the following formulas (Lee, 1976):

$$\boldsymbol{\theta = 2\tan^{-1}\left(\frac{w}{2D}\right)} \qquad \text{Equation 3.2}$$

$$\boldsymbol{\dot{\theta} = \frac{w\,|v_f - v_t|}{D^2 + 4w^2}} \qquad \text{Equation 3.3}$$

In these equations, W is the width of the lead vehicle, D is the distance from the driver's eyes to the back of the lead vehicle, and $|\boldsymbol{v_f - v_t}|$ is the relative speed of the two vehicles. Figure 3.1 shows the visual angle of the lead vehicle at the subject vehicle driver's eyes. As the driver gets closer to the potential hazard, τ^{-1} and visual looming of the lead vehicle on subject vehicle drivers' eye increases.

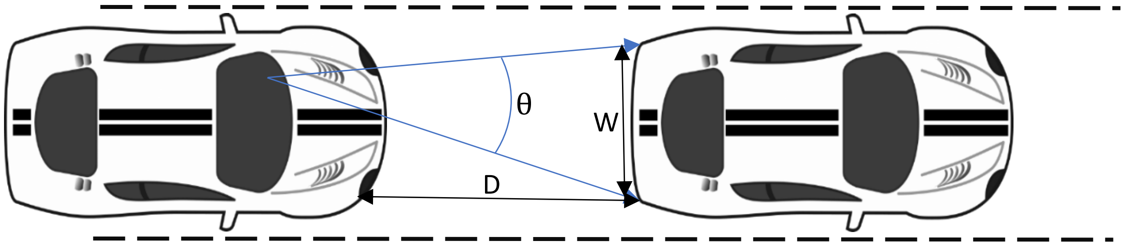

Figure 3.1. Visual angle of lead vehicle at the subject vehicle driver's retinas. Note: θ, W, and D indicate the driver's visual angle of the lead vehicle, width of the lead vehicle, and distance to the lead vehicle, respectively.

In visual evidence accumulation models, drivers receive some evidence such as changes in the visual looming of the lead vehicle. This evidence helps the driver to perform an avoidance action when there is a potential upcoming collision and sufficient evidence is accumulated (Markkula et al., 2018a). The evidence accumulation models in hazard situations are correlated with the process of situation awareness recovery (Goncalves et al., 2019) and are introduced by a dynamic notion of predictive processing (Engström et al., 2018). Predictive processing model indicates that the driver's detection of the need to initiate a response is driven by the difference between actual and expected looming (Engström et al., 2018; Xue et al., 2018); For example, in a situation where the driver is following a lead vehicle, if there is a fixed distance between the subject and lead vehicles, then, the driver predicts that there should be no visual expansion of the lead vehicle. The issue arises when the lead vehicle starts braking or slowing down and causes a mismatch between driver's predicted and actual looming (Victor et al., 2018). The looming prediction error, which drives initiation of control actions (Engström et al., 2018), is defined as:

$$\boldsymbol{\varepsilon(t) = \tau_{actual}^{-1} - \tau_{predicted}^{-1}} \qquad \text{Equation 3.4}$$

In this equation, τ_{actual}^{-1} is the actual looming and $\tau_{predicted}^{-1}$ is the predicted looming. The following equation represents the accumulative part of evidence accumulation models:

$$\frac{\boldsymbol{dA}}{\boldsymbol{dt}} = \boldsymbol{k\varepsilon(t) - M + v(t)} \qquad \text{Equation 3.5}$$

In which, $\varepsilon(t)$ is the looming prediction error, $v(t)$ is a zero-mean Gaussian white noise with standard deviation of σ. $\sigma, k,$ and M are free model parameters. Brake adjustment will be executed if A exceeds a threshold. Previous studies have used this model and estimated the brake reaction times by fitting the model to a set of data and finding the optimal free parameters (Bianchi Piccinini et al., 2020; Svärd et al., 2021). There are, however, several ways in which the model can be further extended based on the driving situation. Therefore, the model parameters are extended based on the suggestions from previous studies and the experimental design in this study. These extensions are further discussed in the method section.

3.1.4.2. Steering model

The steering behavior has not been investigated as much as the braking behavior. However, steering models still have a long history in human behavior and traffic safety (Michon, 1985). A steering maneuver can include a crash avoidance maneuver and a subsequent stabilization maneuver (Merat et al., 2014; Russell et al., 2016). Based on Markkula et al. (2014), the steering avoidance maneuver starts when the lead vehicle starts braking and ends when the driver begins applying considerable rightward steering wheel rotation to transit from leftward collision avoidance to lane alignment and vehicle stabilization in the adjacent lane. Stabilization maneuver begins with the steering wheel rotation and ends either 250 m after passing the lead vehicle, or when the driver's vehicle falls below 10 km/h, whichever happens first. Markkula et al. (2014) compared different closed-loop and open-loop steering models in predicting the avoidance and stabilization steering. Based on the results of this comparison, the open-loop models provided the best fit for the avoidance maneuver, while the closed-loop models better explained the stabilization maneuver.

3.1.5. Research gaps and objective

Results from the survey analysis revealed that FCW, AEB, and BSM are among the most beneficial ADAS based on the officers' opinions (Wozniak et al., 2021). Previous studies have investigated the effects of ADAS technologies such as FCW and BSM on civilian drivers' driving performance and/or workload (Chun et al., 2013; Cicchino, 2017a, 2018; Kusano & Gabler, 2011; Muhrer et al., 2012). While police officers are usually involved in more hazardous driving situations such as driving in high speed, pursuit situations, and complex traffic situations (Zahabi et al., 2021b), there is no study that specifically examines the effects of ADAS technologies on officers' driving performance and workload. Also, results from the TAM suggested that trust in ADAS can significantly increase officers' intention to use the technology. Therefore, there is a need for a study to investigate the effects of FCW/AEB and BSM on police officers' driving performance, workload, and trust in ADAS. Table 3.3 summarizes the hypotheses (H) in this study which were formulated based on the literature review. Although previous studies suggested an improved driving performance with ADAS, it was assumed that ADAS would increase driver workload since officers are not experienced with the ADAS, and a combination of auditory and visual warnings may overwhelm the officers (Wickens, 2008).

Table 3.3. List of hypotheses

Hypotheses number	Description	Reference
H1	When faced with critical incidents (i.e., the braking lead vehicle or the vehicle in blind spot), drivers would exhibit a better driving performance when the ADAS is on.	Wu et al. (2018b)
H2	When faced with critical incidents, drivers would experience a higher level of workload when the ADAS is on.	Chai et al. (2022); Lee and Morgan (1994)
H3	When faced with critical incidents, drivers would report a higher level of trust in vehicle safety when the ADAS is on.	Shahini et al. (2022b); Wu et al. (2018b)
H4	When faced with critical incidents, drivers would exhibit a better driving performance in normal driving as compared to pursuit driving situation.	Shupsky et al. (2020)
H5	When faced with critical incidents, drivers would experience a lower level of workload in normal driving as compared to pursuit driving situation.	Shupsky et al. (2020)
H6	When faced with critical incidents, drivers would exhibit a better driving performance when they are not engaged in a non-driving related task as compared to when they are performing such a task.	Shahini et al. (2022b)
H7	When faced with critical incidents, drivers would experience a lower workload when they are not engaged in a non-driving related task as compared to when they are performing such a task.	Shahini et al. (2020b); Zahabi et al. (2021b)

In addition, some previous studies found that high frequency of unwanted ADAS warnings may induce unintended adverse behavioral effects, and drivers prefer to switch it off (Reinmueller et al., 2020). High frequencies of ADAS warnings can become a more serious issue for police officers as they are required to interact with other in-vehicle technologies such as radio and MCT. Therefore, there is a need for an adaptive FCW that warns officers in specific situations and encourage them to keep it on. Nakaoka et al. (2008) suggested that the critical warning time for FCW is a linear function of the speed of the subject vehicle, speed of the lead vehicle, relative speed of the vehicles, and the driver's brake reaction time. While the speed of the front vehicle can be measured by sensors, the driver brake reaction time may differ based on the criticality of the driving situation. Therefore, the second objective of this study is to build a model to calculate the brake reaction time of the officers to adjust the ADAS warnings when the front vehicle brakes.

Drivers may not notice the BSM icon in their side mirrors in many situations when there is a vehicle in their blind spot. One may propose to issue an auditory warning when there is a vehicle in the blind spot. However, similar to the FCW, it may be annoying to receive an auditory warning whenever there is a vehicle in the blind spot, and officers tend to keep it off. However, it can be beneficial to warn the officers when they are not aware of the vehicle in their blind spot and attempt to change their lane. An auditory warning can be initiated depending on the criticality of the situation and the angle of the steering wheel (i.e., a warning will be initiated if drivers rotate the steering wheel to the extent that they pass a certain threshold). Therefore, the third objective of this study is to build a model to estimate the officers's maximum steering wheel angle when trying to change their lane with a vehicle in their blind spot.

3.2. Method

3.2.1. Driving simulator experiment

3.2.1.1. Participants

The experiment was conducted with 18 police officers (Age: M =37.82 yrs., SD = 5.41 yrs.). The required sample size was estimated as 24 subjects using the G*Power software (Faul et al., 2007) with α=.05, power (1-β) of .8, and using Cohen's medium effect size of .25 (Cohen, 1988). Initially, 24 officers were recruited, however, six officers could not complete the experiment due to simulation sickness. All participants had valid driver license and were sampled from the police officers who regularly drive police vehicles. All participants reported a 20/20 vision or wore contact lenses. Participants were provided with a unidimensional visual analog rating scale to identify their level of experience with police in-vehicle ADAS technologies. They were asked to give a subjective rating by marking a point on a continuous (100 mm) scale with anchors of 'no experience' and 'high experience'. The distance from the left anchor to the marking was measured (with millimeter accuracy) and this distance was transformed to a percentage. Subsequently, the mean of these percentages across all participants was calculated and identified as the average technology experience with FCW (M =28.26%, SD = 31.27%) and BSM (M =34.49%, SD = 29.40%). Table 3.4 provides the demographic information of the participants. Prior to participating in the study, each participant read and signed the informed consent form. The Texas A&M University Institutional Review Board (IRB) approved the study protocol.

Table 3.4. Results of the demographic questionnaire

Category	**Results**
Sex	18 males
Age	*M* = 37.82 yrs., *SD* = 5.41 yrs.
Number of participants who attended police academy	18
Experience as police officer	*M* = 10.78 yrs., *SD* = 3.68 yrs.
Experience serving as a primary patrol officer	*M* = 8.92 yrs., *SD* = 3.62 yrs.
Number of participants who received additional training since the police academy (e.g., emergency vehicle operation courses)	17
Number of participants who had experience in driving simulator studies	6
hours per week in car	*M* = 7.82 hrs., *SD* = 3.73 hrs.
Level of experience with FCW	*M* = 28.26%, *SD* = 31.72%
Level of experience with BSM	*M* = 34.49%, *SD* = 29.40%

3.2.1.2. Apparatus

A fixed-based driving simulator (Realtime technologies, Inc., Ann Arbor, MI) was used in this experiment (Figure 3.2). The simulator consisted of a Ford Fusion mounted platform with a cylindrical projection screen providing 300° field of view and collected driving behavior data with sampling rate of 60 Hz. The SimCreator DX software was used to create the driving scenarios. The NDRT was displayed on a laptop and the participant could interact with it by using the keyboard (Figure 3.2).

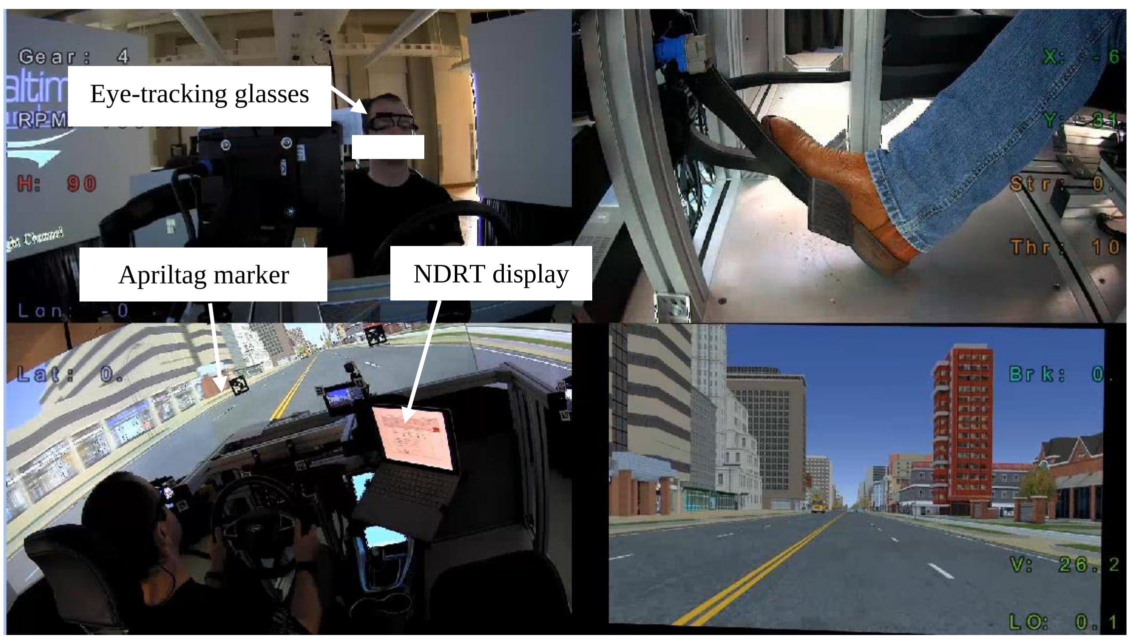

Figure 3.2. Driving simulator setup

A Pupil-core eye tracking system (Pupil Labs, Germany) was used to collect driver pupil data (Figure 3.2). The system hardware consisted of one world camera and two eye cameras. The eye cameras detect and track the pupil with 3-dimensional models. Gaze parameters were gathered in normalized 3D gaze positions and binocular vergence.

Eye movements were recorded with .6 degrees accuracy, .02 precision, and frequency of 200Hz. The pupil was calibrated using Apriltag markers. Dismissing rate during the calibration was consistently controlled to be less than 20% based on the criteria defined by the manufacturer (Pupil Labs). The pupil size was calculated by measuring the relative size in eye camera pixels in millimeter unit in the 3D eye model. Polar H10 chest strap was used to capture the RMSSD.

3.2.1.3. Independent variables

The independent variables manipulated in this study included: (1) ADAS type (FCW/AEB, BSM, and a combination of FCW/AEB and BSM) (2) ADAS technology status (ON/OFF) (3) driving condition (normal vs. pursuit), and (4) NDRT (ON/OFF). Each of the scenarios included two data blocks and officers were asked to complete the NDRT in one of the blocks randomly. Therefore, the status of the NDRT was manipulated within each scenario.

For the FCW/AEB activated scenarios, the scenarios were designed to form a rear end pre-crash situation. A braking lead vehicle was used as the critical incident to mimic a naturalistic and frequent accident scene. Lead vehicles have been widely used as critical incidents in previous studies (Gold et al., 2013; Happee et al., 2017). The lead vehicle was on the same lane as the subject vehicle. Initially, the leading vehicle would keep a fixed headway time (2.5 s) with the subject vehicle. A headway of 1.7–2.5 s is the typical headway range based on the previous studies (Abe & Richardson, 2004, 2006; Lee et al., 2002; Wu et al., 2018c). When the leading vehicle suddenly initiated a hard brake, FCW was activated and a combination of an auditory (i.e., beep) and visual warning was issued to warn the driver (Figure 3.3). Also, the system would apply the emergency braking along with the warning. The critical situation needed the driver to properly respond to the leading vehicle by pressing the brake, rotating the steering wheel, or a combination of both. A similar scenario without the FCW and with the same hazard was built to compare the manual vs. FCW activated conditions.

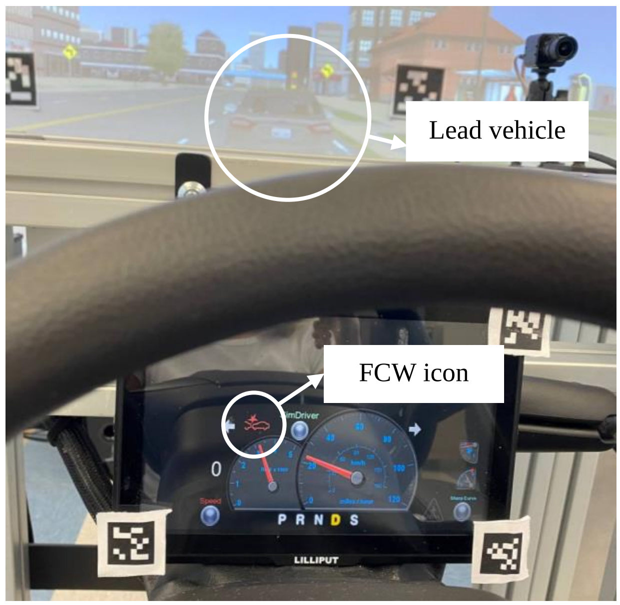

Figure 3.3. FCW icon

In scenarios where the BSM was activated, a similar hazard (i.e., a lead vehicle suddenly brakes) was used to block the drivers' path and force them to change their lane. In addition, another vehicle was added to the adjacent lane in the blind spot of the subject vehicle to mimic a critical situation and activate the BSM warning. Similar hazards were used in previous studies (Chun et al., 2013). If there was an object in the blind spot, an icon was shown at the bottom right/left of the right/left mirror (Figure 3.4). If drivers turned their blinkers on, an auditory (i.e., beep) message would be initiated. A similar scenario without BSM warning and with the same hazard was built to compare the situations with and without ADAS.

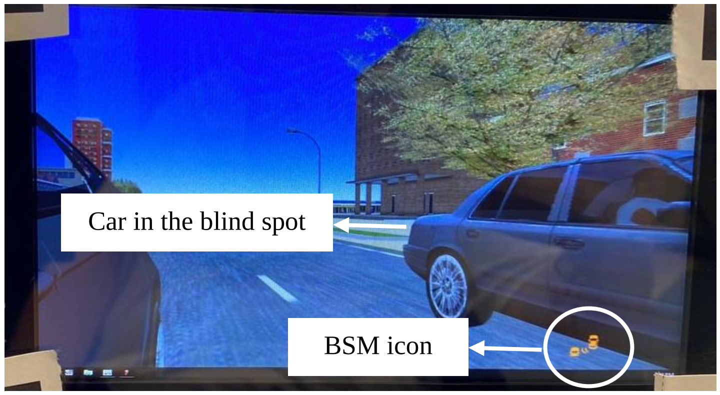

Figure 3.4. BSM warning icon

For the combination of FCW/AEB and BSM, a combination of both a braking lead vehicle and a vehicle in blind spot was used to mimic a critical situation and assess the effects of ADAS technologies. Both FCW and BSM warnings as well as AEB were active in this scenario. In this experiment, the ADAS warnings were designed to function flawlessly, showcasing an accuracy rate of 100% and effectively preventing any occurrence of false alerts. A similar scenario without any warning and with the same hazard was built to compare with the findings of this condition.

3.2.1.4. Experimental design

The experiment followed a within-subject design including 12 driving scenarios (3 ADAS type (FCW/AEB, BSM, and a combination of FCW and BSM) × 2 ADAS status (ON/OFF) × 2 driving conditions (normal vs. pursuit)). Each scenario used a different path to avoid learning effects from one scenario to the next. However, all scenarios were simulated in an urban environment with the same traffic level and road conditions to ensure similar level of difficulty.

Each driving scenario included two critical hazards in random sections of the path, and the drivers were asked to react immediately to avoid the critical incident by pressing the brake or changing their lane by turning the steering wheel. The critical incidents happened at least one minute after the start of each scenario, and there was at least a two- minute time lapse between the two critical events. In addition, drivers were engaged in a NDRT twice in each scenario: once in combination with the critical incident and once in a similar section of the road without an incident to avoid learning effects and predicting the hazard.

3.2.1.5. Driving scenarios

Participants were instructed to drive the simulated urban roadway (Figure 3.5), follow all traffic rules, maintain their vehicle in the middle of the right lane all the time (except when maneuvering at intersections or taking over the lead vehicle), and maintain the speed of 40 mph in the normal driving condition. Also, they were asked to start chasing the fleeing vehicle with the maximum speed of 60 mph when they hear the auditory message. To accommodate the limitations of the driving simulator and prevent simulation sickness, officers were requested to drive at a maximum speed of 60 mph, which is a restriction, despite their capability of reaching speeds up to 100 mph in real-world driving. Nevertheless, we encouraged officers to emulate their usual driving style as closely as possible, replicating real-world conditions.

The order of driving scenarios was randomized to avoid any learning effects. The simulation was designed to represent a realistic urban driving environment with four lanes, following regulations published by the Roadway Design Manual of Texas Department of Transportation (TxDOT, 2020). Each driving scenario was approximately 6 minutes, and included two critical incidents and the location of critical incidents varied among the trials to limit any potential learning effect from one trial to another (Zahabi & Kaber, 2018a).

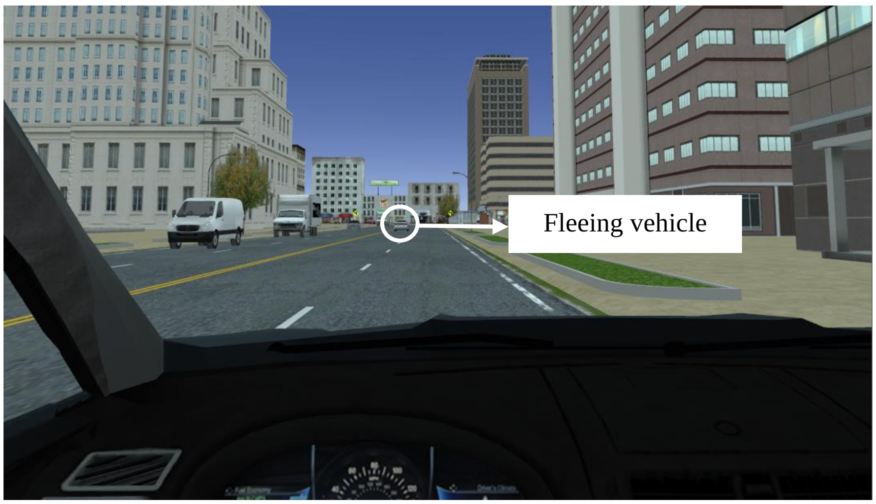

Figure 3.5. An example of driving scenario

3.2.1.6. Non-driving related task

A plate number check task was used as an NDRT. This task is the most frequently performed in-vehicle task for the officers (Zahabi et al., 2022). In this task, an automated voice from the simulator provided a question regarding a vehicle (e.g., "what is the plate status?"). The questions were designed based prior studies and interviews with police officers (Shupsky et al., 2020; Zahabi & Kaber, 2018b). Once the auditory question was played, the participant searched for the information on the MCT (by pressing the arrow keys to go to different information pages and reading the information on each page). The task completed once the officer verbally provided the answer, and their response was recorded by the camera. The MCT interface prototype was designed based on the MCT interface used by Texas police departments to ensure all officers were familiar with the layout (Figure 3.6).

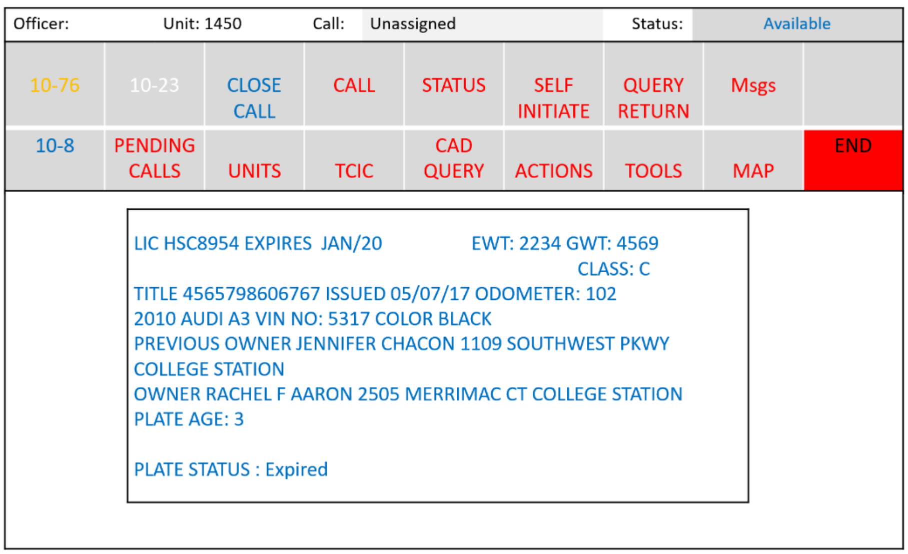

Figure 3.6. The MCT screen with a sample NDRT (plate number check task)

3.2.1.7. Dependent variables

The dependent variables included driver performance, NDRT performance, cognitive workload, and driver trust. Driver performance measures for scenarios with FCW/AEB included brake reaction time, minimum TTC (Saffarzadeh et al., 2013; Wan & Wu, 2018), maximum lateral acceleration (Gold et al., 2013; Wan & Wu, 2018), and maximum longitudinal deceleration (Dogan et al., 2019; Wan & Wu, 2018). TTC was defined as the time that the two vehicles would have a collision if they continued at their present speed and on the same path and was used as an indicator of the potential crash severity based on Hirst (1997). Lateral acceleration was used to assess the quality of driving performance and vehicle stabilization when passing the lead vehicle based on Gold et al. (2013). Maximum longitudinal deceleration was used to measure the severity of the brake reaction. Brake reaction was measured as the time between the lead vehicle braking and the driver pressing the braking pedal (Bakowski et al., 2015). Driver performance measures for scenarios with BSM included number of collisions and time to change lane (Chun et al., 2013).

Driver workload was measured using both physiological (i.e., average blink rate, PCPS, and RMSSD) and subjective measures (i.e., DALI questionnaire) (Appendix A). Under conditions of controlled illumination by researchers, previous studies found that pupil size is a useful and reliable measure of mental workload, which increases in pupil size correlate with increases in mental workload (Brookhuis & De Waard, 2010; Iqbal et al., 2005). The experiment was conducted in a room where light and noise levels were well-controlled. PCPS was calculated by subtracting the baseline pupil size (collected prior to the experiment and when the driver was seated in the cab and relaxed) from the measured pupil size in each trial and then dividing by the baseline pupil size. The baseline pupil size was measured while participants were looking at the screen (i.e., a static image of a roadway without any traffic). RMSSD was obtained by first calculating each successive time difference between heartbeats in milliseconds. Then, each of the values was squared and the result was averaged before the square root of the total was calculated. While the conventional minimum recording for RMSSD is 5 min, researchers have proposed ultra-short-term periods of 10 s (Salahuddin et al., 2007), 30 s (Baek et al., 2015), and 60 s (Esco & Flatt, 2014).

To measure the NDRT performance, task completion time was recorded. In addition, NDRT performance was used as a secondary measurement for workload (Shahini et al., 2021).

The present study evaluated the cognitive measure of explicit trust (i.e., evaluations that a person has) via a subjective questionnaire. To explicitly evaluate trust in automation, a 20-item questionnaire was adapted from previous studies (Forster et al., 2017; Gold et al., 2015; Verberne et al., 2012) and supplemented with self-created items (Appendix B). The 20 items were rated on a 7-point Likert scale ranging from 1 (strong rejection) to 7 (strong approval). The questionnaire can be broken down into three subscales based on theoretical implications on trust in automation by Lee and See (2004). These subscales include performance (i.e., what does the automation do?), process (i.e., how does the automation operate?) and purpose (i.e., why was the automation developed?). It is crucial to clarify that officers were requested to assess their confidence in the overall safety of the vehicle, rather than specifically evaluating the functionality, failure, or activation of the ADAS. In the questionnaire, participants were instructed to interpret the term "system" as referring to the vehicle itself, rather than solely focusing on the ADAS.

3.2.1.8. Procedure

Prior to the experiment, all participants completed and signed the informed consent form and the demographic questionnaire. The simulator sickness questionnaire was used to measure any potential motion sickness symptoms prior to the study (Kennedy et al., 1993). Participants were trained to use the driving simulator. The training trials included simulation of an urban driving environment similar to the experiment scenarios. At the end of the training, driver speed and lane deviations were calculated across trials to guarantee conformance with established performance criteria, including $|\text{lane deviation}| \leq 1.37$ ft and $|\text{speed deviation}| \leq 1$ mph (Horrey & Wickens, 2004).

Once the participants passed the training criteria, they were provided with instructions on the NDRT. Then, they were asked to watch a training video about the application of the FCW/AEB, and BSM. The video included the definition, application, and type of the ADAS warnings used in this study. Once participants watched the video and were familiar with the ADAS, they completed another practice scenario that included use of NDRT, a pursuit driving condition, and application of FCW/AEB and BSM. After the training, drivers were administered another simulator sickness questionnaire to ensure absence of simulator sickness symptoms. In addition, they were provided with the DALI pairwise comparison sheet to identify the relative weight of different workload contributors. Subsequently, the eye tracking system was calibrated for the participants and the baseline pupil size was captured for 2 min. while participants were seated in the cab.

For the experiment trials, participants were instructed that driving was the primary task and they needed to complete the NDRT using the side screen as accurately and quickly as they could. In addition, they were instructed to follow the fleeing vehicle as soon as they hear the warning "follow the white vehicle". They were also told that critical incidents could occur during trials. They were instructed that once the lead vehicle brakes, they should react as quickly and as safely as possible to avoid a potential collision by pressing the brake pedal, rotating the steering wheel, or a combination of both. After each trial, they were asked to complete the DALI and trust questionnaires. Participants were provided with a 3-min break between trials. The simulator sickness questionnaire was evaluated again after the trial. The experiment took approximately 2.5 hours to complete and all participants were paid $70 for their participation.

3.2.2. Models of driver behavior

3.2.2.1. Braking model

As mentioned in the introduction, there are several ways to extend the braking model depending on the driving conditions. For example, cognitive load imposed by performing the NDRT with MCT can strongly affect driver brake reaction time. Unexpected braking of the lead vehicle is a non-practiced task and thus relies on cognitive control, and can be impaired by cognitive overload. Cognitive overload caused by using an NDRT can interfere with the cognitive resources required for braking and therefore, can affect driver reaction time. Previous studies suggested that the effect of NDRT depends on the initial time headway because cognitively-loaded drivers respond based on kinematic dependent looming cues (Engström et al., 2017). Therefore, it can be assumed that being engaged in a NDRT can affect the brake response time by changing visual looming of the lead vehicle on drivers' retina.

Pursuit driving condition requires both operational (e.g., lane keeping, following the lead vehicle) and tactical driving behavior (e.g., passing maneuvers or overtaking) and is more demanding than the normal condition that only involves operational driving behavior (Shupsky et al., 2020). In addition, in pursuit driving conditions, officers drive at high speed, change lanes, and perform sudden maneuvers as compared to the normal driving condition. Therefore, it is expected that officers experience a higher workload in the pursuit condition than the normal driving condition. Regarding the effects of pursuit condition on officers' driving performance, Zahabi et al. (2021a) found that driving in pursuit condition can degrade officers' performance as shown by higher speed deviation and lane deviation. Based on Engström et al. (2017), cognitive load can impair braking in response to expected brake lights by affecting the visual looming. Therefore, it can be concluded that the cognitive load imposed by the pursuit condition may have an effect on the visual looming component of the braking model.

In addition, Shupsky et al. (2020) suggested that the effects of in-vehicle technologies such as MCT may pose an additional threat to the driving task and are additive in nature, especially in more complicated situations such as pursuit driving. Therefore, it can be assumed that there is an interaction effect of pursuit driving situation and NDRT on visual looming in the braking model. The following equation represents the final evidence accumulation model suggested by this study:

$$\boldsymbol{\frac{dA}{dt} = k\varepsilon(t)(1 + \rho * P(t) + \eta * N(t) + N(t) * P(t) * \gamma) - M + v(t)} \qquad \text{Equation 3.6}$$

In which, $\varepsilon(t)$ is the looming prediction error, $v(t)$ is a zero-mean Gaussian white noise with standard deviation of σ, M is a constant, k is a constant, ρ represents the effect of pursuit driving, η represents the effect of NDRT, and γ represents the interaction effect between pursuit situation and NDRT. σ, M, k, ρ, η, and γ are free model parameters. Brake adjustment will be executed if A exceeds a threshold. $P(t)$ and $N(t)$ are binary variables that can get a value of 1 if the officer drives in the pursuit situation or is engaged in an NDRT and can get a value of 0 if the officer drives in the normal situation and is not engaged in an NDRT respectively.

The braking model parameters were optimized through a grid search across a set of fixed values for σ, M, k, ρ, η, and γ for evidence accumulation in brake reaction time model. Table 3.5. illustrates the range of the search for each parameter. The model was run for each combination of the parameters, resulted in a distribution of brake reaction times per scenario. The best combination of parameters for the brake reaction model was selected based on the smallest root mean square error (RMSE) over all scenarios.

Table 3.5. Parameters search range for brake reaction model

Parameter	Searched range
σ	[0.1,1]
M	[-1,1]
k	[1,8]
ρ	[-0.5,0.5]
η	[-0.5,0.5]
γ	[-0.5,0.5]

Ranges for σ, M, and k were determined using a manual search and the suggestions from previous studies (Markkula et al., 2018b). Ranges for ρ, η, and γ, however, were determined based on the empirical and theoretical findings from the previous studies (Engstrom et al., 2017). Based on the cognitive load theory proposed by Engström et al. (2017), performance on non-practiced or naturally variable tasks, relying on cognitive control, is consistently impaired by cognitive load, whereas the performance on automatic (well-practiced and consistently mapped) tasks is unaffected and sometimes even improved. One may suggest that braking response to a braking lead vehicle is a well-practiced and automated task for law enforcement officers. However, the scenarios in this experiment were not practiced before and therefore, the task can be assumed as a non-automatic task. Also, a meta-analysis by Engström (2010) found that the effects of cognitive load on brake response time reported in experimental lead vehicle braking studies appears to depend strongly on scenario kinematics, in terms of the initial time headway. Therefore, a range of negative, zero, and positive values for ρ, η, and γ was included in the analysis.

In addition, a comparison of the model accuracy between the basic model (i.e., the model including $\sigma, M,$ and k) and the full model (i.e., the model including σ, M, k, ρ, η, and γ) was conducted to evaluate the effectiveness of the additional parameters (i.e., ρ, η, and γ) on model improvement.

3.2.2.2. Steering model

Based on Markkula et al. (2014), the open-loop models provided the best fit for avoidance maneuver. The steering model in this experiment predicts the maximum steering wheel angle when officers drive with BSM and try to change their lane when there is a vehicle in their blind spot. Therefore, the avoidance phase model is suitable for the purpose of this study without the consideration of the stabilization phase. Breuer

(1998) found that in an evasive maneuver, the amplitude of steering wheel angle and maximum rate of the steering angle are linearly correlated which suggests a constant duration of steering corrections (Markkula, 2014). The steering wheel angle rates in open loop avoidance models follow a Gaussian distribution function (Markkula, 2015) as defined by Equation 3.7.

$$\dot{\delta} = Ae^{-(\frac{(t-\mu)^2}{2\delta^2})} \qquad \text{Equation 3.7}$$

In this Equation, $\dot{\delta}$ denotes the changes in the steering wheel angle, A is the amplitude of the pulse based on a constant variable k and maximum visual looming after the event onset and prior to the avoidance maneuver initiation, μ is the mean of the model input and was set to the time $T_S + T_A$ where T_S is the time when the steering input reaches half of its maximum value, and δ is the standard deviation of the model and was a function of time duration (T_H). Following the work in Markkula et al. (2014), k, T_A, and T_H are considered as free parameters. By fitting this model to the experimental data, the free parameters will be adjusted. Table 3.6. illustrates the range of the search for each parameter.

Table 3.6. Parameters search range for steering wheel model

Parameter	Searched range
k	[0,50]
T_A	[1,10]
T_H	[0.1,1]

3.2.3. Data analysis

Before conducting any inferential statistical tests, the data on driving performance, eye tracking data, heart rate data, DALI score, and trust score underwent a data screening process to identify any outliers. The outliers were removed based on the review of video recordings and Cook's D criteria. The dependent variables were also subjected to diagnostic tests to ensure that they met parametric test assumptions of normality and equal variance. The normality of residuals was inspected using normal probability plots and Shapiro-Wilk's Goodness-of-Fit tests, while variance homoscedasticity was assessed using Bartlett's tests. In case of violations of parametric assumptions, the data underwent Box-Cox transformation (maximum lateral acceleration, minimum TTC, time to change lane, PCPS, blin rate, and RMSSD) or fourth power transformation (maximum longitudinal deceleration). If the data transformation did not resolve the assumption violations, the data were ranked, and non-parametric procedures were used (trust score).

Covariates such as age, experience in automated driving studies, experience as a police officer, experience as a primary patrol officer, experience with ADAS, experience with automated vehicles, and trial number (1-12) were included in the model and removed if found to be insignificant. An analysis of variance (ANOVA) was conducted to examine the impact of explanatory variables on response variables, and Tukey's Honest Significant Difference (HSD) post-hoc multiple comparison was applied to identify any significant differences among levels of significant effects. A significance level of $p<0.05$ was set as a criterion for the study. The standard errors are represented by error bars in Figures, and letters (A, B, C) were used to indicate significant differences between groups based on post-hoc analysis. The driving simulator provided driving performance responses in seconds with accuracy up to two decimal digits, and R studio was used to conduct the inferential statistics.

Twenty-three (23) out of 398 driving performance data points were removed due to participants not following instructions, going the wrong way, driving through the lead vehicle, or not waiting for the lead vehicle to brake. Seven crashes with the lead vehicle were recorded, and 34 brake data points were removed due to participants not braking when negotiating hazards. Twelve secondary task completion times were dropped because participants did not know they needed to answer or did not hear the question. A total of 34 PCPS data points and 57 blink rate data points were excluded from the study. The reasons for exclusion were related to eye recording failure, driving simulator failure, or low confidence level. These data points were removed from the analysis to ensure the accuracy and reliability of the data used for inferential statistical tests.

3.3. Results

3.3.1. Driving simulator

3.3.1.1. Driving performance

Brake reaction time

There were no significant main effects of ADAS status ($F(1, 171.99) = 1.26$, $p = .26$, $\eta^2 = .007$), ADAS type ($F(1, 175.46) = 0.94$, $p = .33$, $\eta^2 = .005$), driving condition ($F(1, 173.78) = 1.39$, $p = .24$, $\eta^2 = .008$), or NDRT ($F(1, 171.62) = 0.22$, $p = .64$, $\eta^2 = .001$) on participants' brake reaction time.

Maximum lateral acceleration

The ANOVA results indicated that the participants' maximum lateral acceleration was significantly affected by the ADAS type ($F(1, 174.79) = 5.47$, $p = .02$, $\eta^2 = .03$) (Figure 3.7), and driving condition ($F(1, 173.24) = 17.88$, $p < .001$, $\eta^2 = .09$) (Figure 3.8). There were significant interactions between the ADAS type and driving condition ($F(1 , 173.24) = 4.45$, $p = .03$, $\eta^2 = .03$) (Figure 3.9), and between the ADAS status and driving condition ($F(1 , 171.76) = 5.69$, $p = .02$, $\eta^2 = .03$). There was no significant effect of ADAS status ($F(1, 171.82) = 1.33$, $p = .25$, $\eta^2 = .01$) or NDRT ($F(1, 171.62) = 0.07$, $p = .79$, $\eta^2 = .001$) on officers' maximum lateral acceleration.

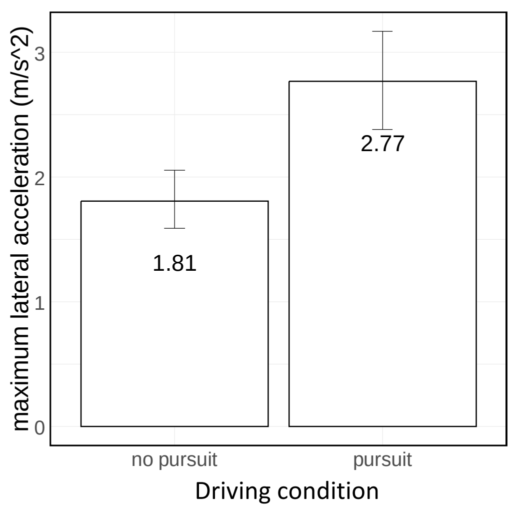

Figure 3.7. Effects of driving condition on maximum lateral acceleration

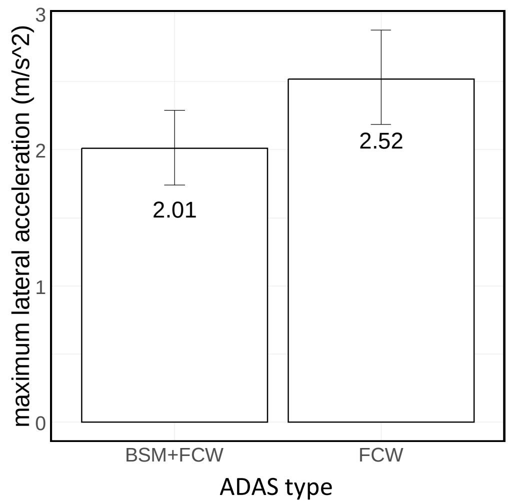

Figure 3.8. Effects of ADAS type on maximum lateral acceleration

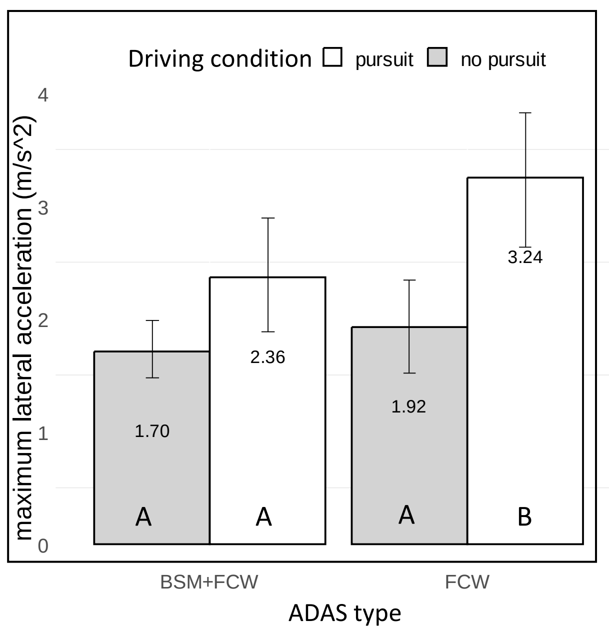

Figure 3.9. Interaction between ADAS type and driving condition on maximum lateral acceleration

Maximum longitudinal deceleration

The findings indicated that the officers' maximum longitudinal acceleration when handling the hazard was not significantly affected by the status of ADAS (F(1, 172.42) = 0.94, p = .33, η^2 = .01), the type of ADAS (F(1, 173.65) = 2.11, p = .15, η^2 =

.01), or the NDRT ($F(1, 172.45) = 0.04$, $p = .83$, $\eta^2 = .001$). However, a significant main effect was observed for the driving condition ($F(1, 173.61) = 33.91$, $p < .001$, $\eta^2 = .16$) (Figure 3.10). Additionally, the ANOVA results demonstrated a significant interaction between ADAS type and status ($F(1, 174.34) = 4.68$, $p = .03$, $\eta^2 = .03$) (Figure 3.11).

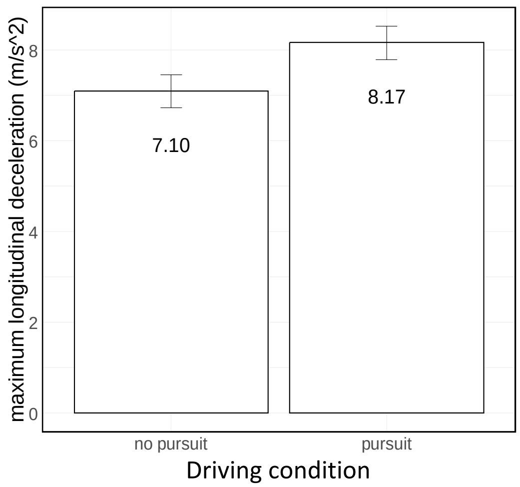

Figure 3.10. Effects of driving condition on maximum longitudinal deceleration

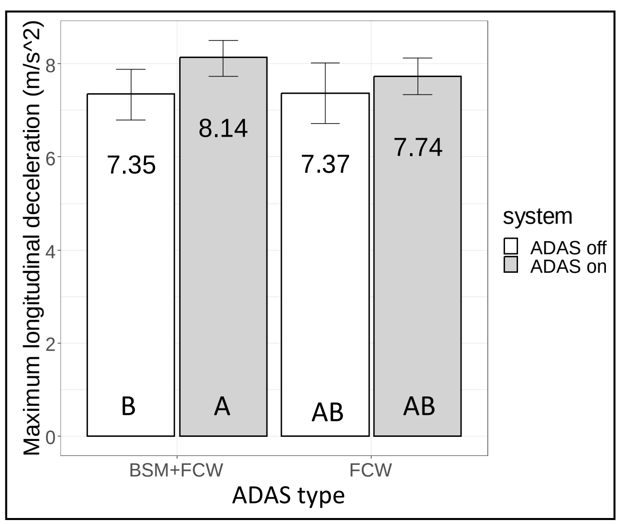

Figure 3.11. Interaction between ADAS type and status on maximum longitudinal deceleration

Minimum time to collision

ADAS status ($F(1, 172.33) = 7.09$, $p = .008$, $\eta^2 = .04$) (Figure 3.12) and driving condition ($F(1, 174.78) = 68.34$, $p < .001$, $\eta^2 = .28$) (Figure 3.13) had significant effects on the minimum time to collision among officers. However, there was no significant main effect of ADAS type ($F(1, 173.73) = 0.22$, $p = .64$, $\eta^2 = 0.001$) or NDRT ($F(1, 172.28) = 0.02$, $p = .89$, $\eta^2 < 0.001$) on the response.

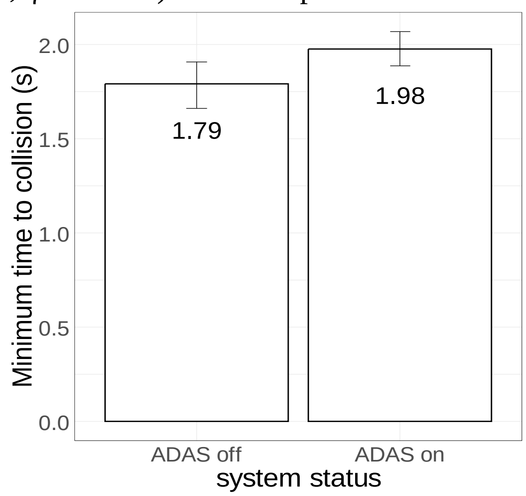

Figure 3.12. Effects of ADAS status on minimum time to collision

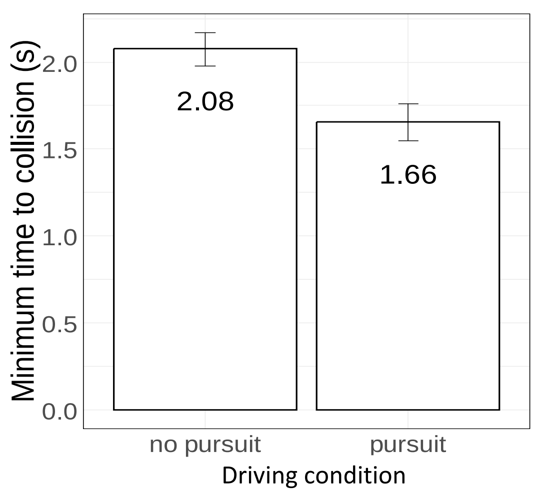

Figure 3.13. Effects of driving condition on minimum time to collision

Time to change lane

The results of the ANOVA revealed a significant main effect of driving condition (F(1, 194.53) = 5.93, p = .02, η^2= .03) on time to change lanes (Figure 3.14). Additionally, there was a marginally significant main effect of NDRT (F(1, 192.37) = 3.52, p = .06, η^2= .02). Officers' time to change their lane decreased with time (F(1, 199.83) = 6.63, p = .01, η^2 = .03). No significant main effects were found for the ADAS status (F(1, 193.90) = 0.26, p = .61, η^2 = .001) or ADAS type (F(1, 194.94) = 0.70, p = .40, η^2= .004), nor were any significant interactions found.

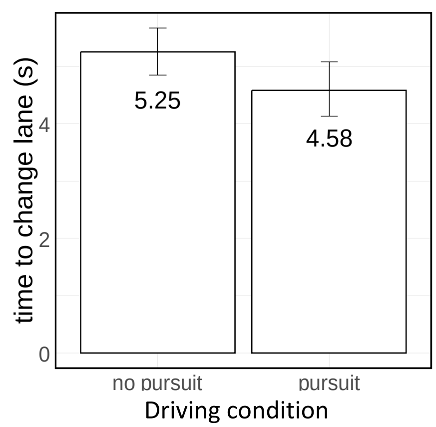

Figure 3.14. Effects of driving condition on time to change lane

3.3.1.2. Workload

DALI

The results indicated a significant main effect of ADAS type (F(2, 132.53) = 3.39, p = .04, η^2= .05) (Figure 3.15), and driving condition (F(1, 132.21) = 68.56, p < .001, η^2 = .34) (Figure 3.16). Additionally, there was a significant effect of participant age (F(1, 10.92) = 9.77, p = .01, η^2 = .47), as well as significant effects of participant experience as a police officer ($F(1, 10.85) = 4.9$, $p = .05$, $\eta^2 = .31$) and participant experience with forward collision warning ($F(1, 10.83) = 4.62$, $p = .05$, $\eta^2 = .30$). Additionally, there was a significant interaction among ADAS type, status, and driving condition ($F(2, 132.271) = 1.79$, $p = .04$, $\eta^2 = .05$). Officers reported a significantly lower workload when BSM and FCW/AEB system were on (M=2.64) as compared to driving without ADAS (M=3.09) in normal driving. All other main effects and interactions were not significant.

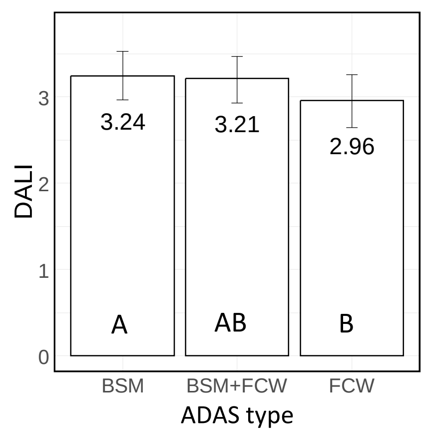

Figure 3.15. Effects of ADAS type on DALI

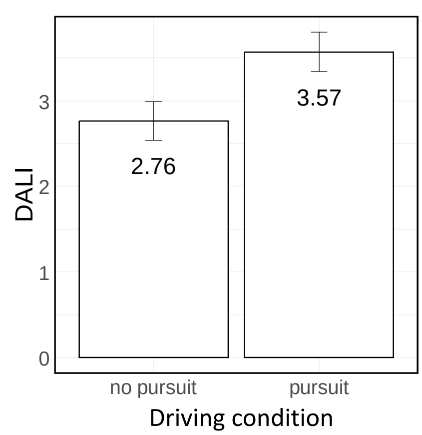

Figure 3.16. Effects of driving condition on DALI

RMSSD

There was no significant effect of ADAS status ($F(1, 264.10) = 0.60$, $p = .44$, $\eta^2 = .002$), driving condition ($F(1, 263.88) = 0.35$, $p = .55$, $\eta^2 = .001$), ADAS type ($F(2, 263.98) = 2.47$, $p = .09$, $\eta^2 = .02$), or NDRT ($F(1, 263.91) = 0.03$, $p = .87$, $\eta^2 < .001$) on the RMSSD response.

PCPS

The ANOVA results revealed that the trial number ($F(1, 310.21)=11.23$, $p= .001$, $\eta^2= .03$), ADAS type ($F(2, 308.74)=3.99$, $p= .02$, $\eta^2= .03$) (Figure 3.17), driving condition ($F(1, 308.19)=11.02$, $p= .001$, $\eta^2= .03$) (Figure 3.18), and NDRT ($F(1, 308.00)=5.17$, $p= .02$, $\eta^2= .02$) (Figure 3.19) had significant main effects on PCPS. Additionally, there was a significant interaction effect between ADAS type and NDRT ($F(2, 308.02)=3.80$, $p= .02$, $\eta^2= .02$) (Figure 3.20) and between driving condition and NDRT ($F(1, 308.01)=7.91$, $p= .005$, $\eta^2= .03$) (Figure 3.21).

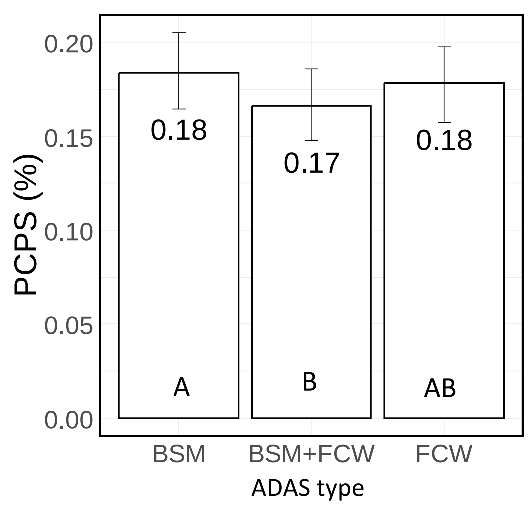

Figure 3.17. Effects of ADAS type on PCPS

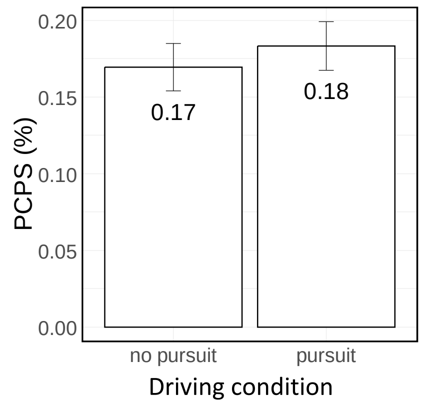

Figure 3.18. Effects of driving condition on PCPS

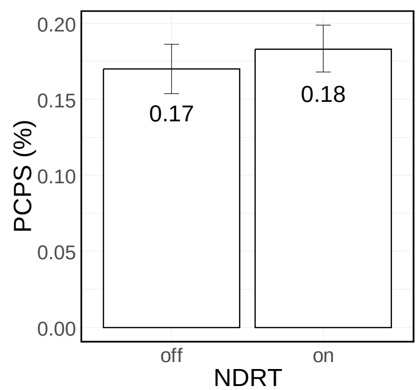

Figure 3.19. Effects of NDRT on PCPS

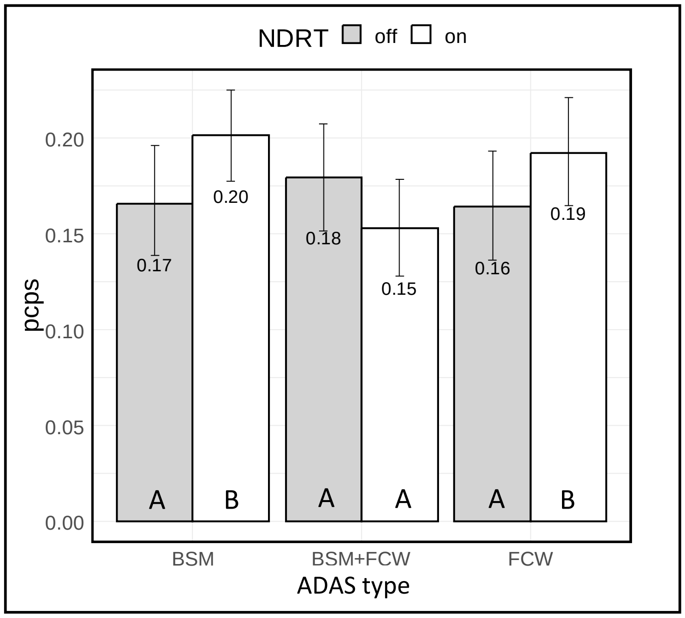

Figure 3.20. Effects of interaction between NDRT and ADAS type on PCPS

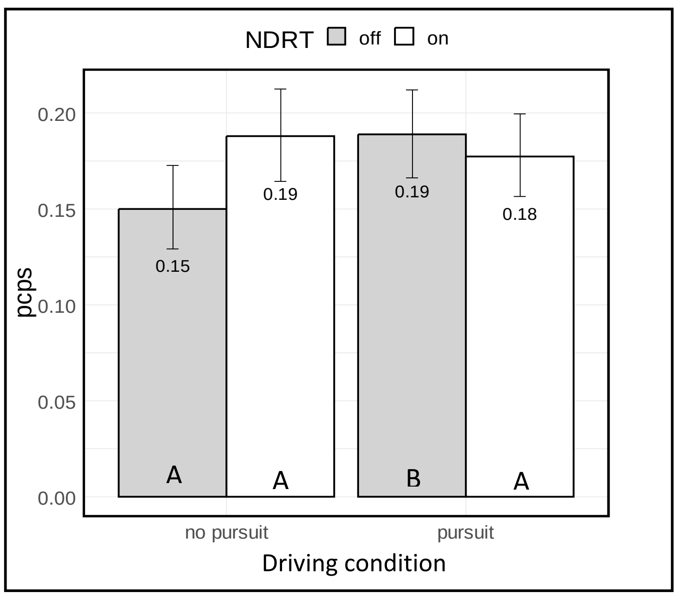

Figure 3.21. Effects of interaction between NDRT and driving condition on PCPS

Blink rate

The results revealed significant effects of trial number ($F(1, 277.12) = 14.85$, $p < .001$, $\eta^2 = .05$), driving condition ($F(1, 275.25) = 7.83$, $p = .006$, $\eta^2 = .03$) (Figure 3.22), and NDRT ($F(1, 275.10) = 20.56$, $p < .001$, $\eta^2 = .07$) (Figure 3.23). No significant main effects were found for ADAS status ($F(1, 275.81) = 0.06$, $p = .800$, $\eta^2 < .001$) and ADAS type ($F(2, 275.65) = 0.10$, $p = .907$, $\eta^2 < .001$).

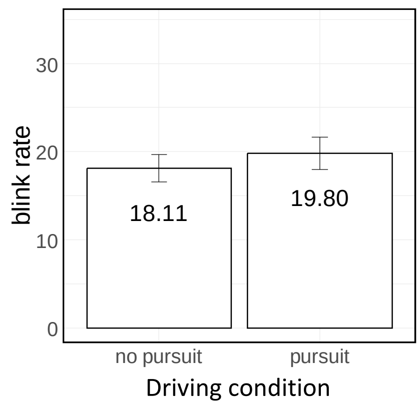

Figure 3.22. Effects of driving condition on blink rate

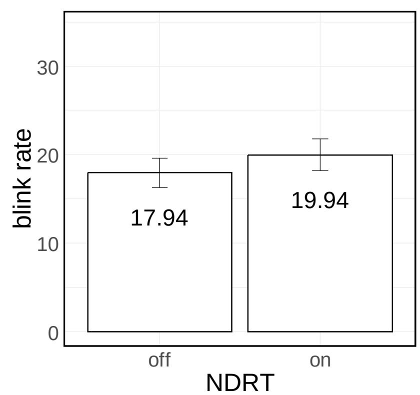

Figure 3.23. Effects of NDRT on blink rate

Trust

There was a significant main effect of ADAS status ($F(1, 297.15) = 18.02$, $p < .001$, $\eta^2 = .06$) (Figure 3.24) and driving condition (F(1, 297.17) = 8.96, p = .003, η^2 =

.03) (Figure 3.25). Nonetheless, the ADAS type did not yield a significant result ($F(2, 297.37) = 0.95$, $p = .386$, $\eta^2 = .006$). Additionally, there was a significant interaction between ADAS status and type ($F(2, 297.43) = 6.84$, $p = .001$, $\eta^2 = .04$).

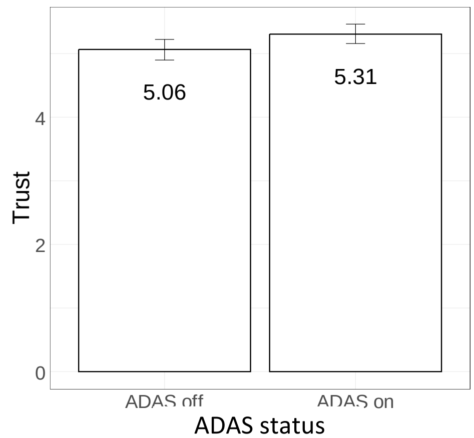

Figure 3.24. Effects of ADAS status on trust score

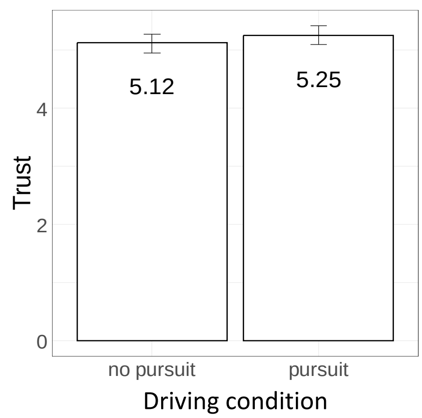

Figure 3.25. Effects of driving condition on trust score

3.3.2. Model results

3.3.2.1. Brake reaction model

The optimal set of parameters in the braking reaction model was selected by finding the smallest difference between predicted reaction times from the model and observed braking reaction times, as measured by the Kolmogorov-Smirnov test

(Appendix C). The values of σ, M, k, ρ, η, and γ that resulted in the best model fit for the full model were found to be σ=0.35, M=-0.35, k=7.5, ρ=-0.1, η=-0.1, and γ=-0.1. The values of σ, M, k, ρ, η, and γ that resulted in the best model fit for the basic model were found to be σ=0.35, M=-0.5, k=7. Additionally, Table 3.7 presents a comparison of the root mean square error (RMSE) between the basic and full models.

Table 3.7. Model fitting results for brake reaction time model

Model	RMSE
Basic model	0.082
Full model	0.069

Results from Kolmogorov–Smirnov (KS) test revealed that the observed data and the predicted values by both basic ($p=0.91$, $D=0.11$) and full model ($p=0.19$, $D=0.22$) came from a same distribution as the experimental data. However, the RMSE of the full model was smaller than the basic model, implying that the full model has better predictive accuracy (table 3.7). Figure 3.26 illustrates the Cumulative density function (CDF) plots vs. brake reaction time with a histogram of the basic and full models compared to the experimental data.

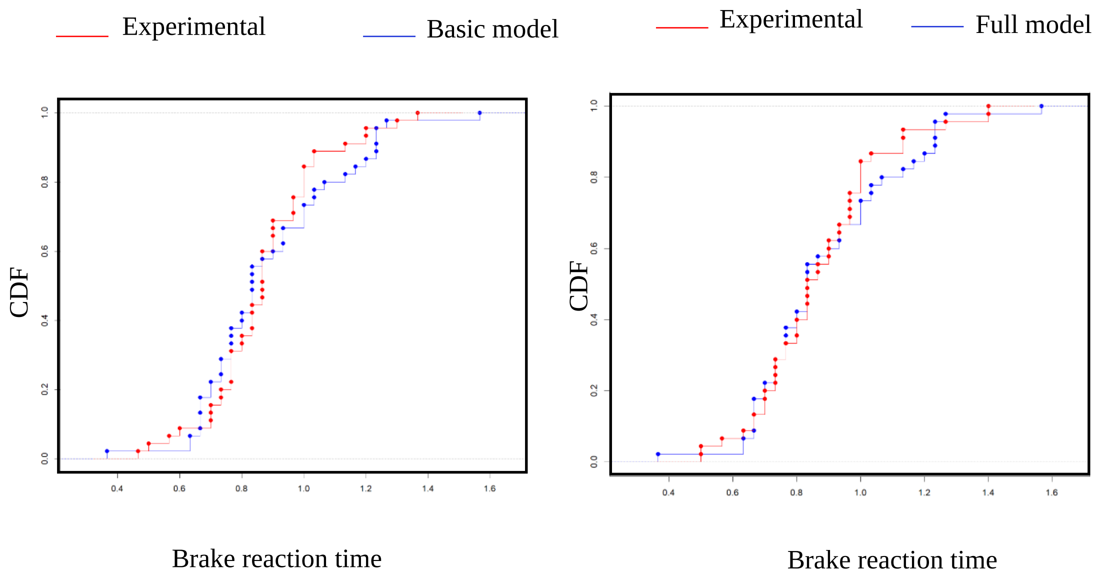

Figure 3.26. Cumulative density function plots of the basic accumulation model, full accumulation model, and experimental data distributions.

3.3.2.2. Steering wheel model

Results from the steering wheel model optimization suggested that $k = 15$, $T_H = 0.6$, and $T_A = 7$ leads to the minimum RMSE (M= 0.023, SD=0.02). The R^2 for this model was computed as 0.67. Figure 3.27 illustrates some examples of the avoidance steering angle versus predicted values by the model.

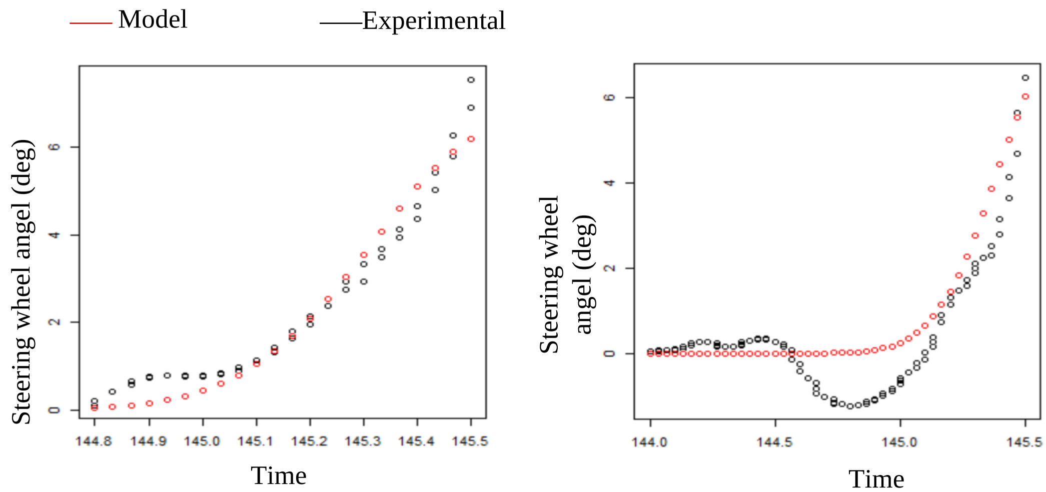

Figure 3.27. Examples of avoidance steering maneuver for the experimental data and fitted model. The red and black dots represent the model and experimental data, respectively. The first example represents a good fit and the second example represent a relatively poor fit.

3.4. Discussion

3.4.1. Driving simulator study

The first objective of the driving simulation study was to investigate the effects of ADAS on officers' performance, workload, and trust. An inferential statistical analysis was conducted to evaluate these effects.

Hypothesis 1 posited that drivers would exhibit a better driving performance with ADAS as compared to driving without ADAS when the lead vehicle brakes. The results partially supported this hypothesis. The results suggested that drivers exhibited an average larger minimum TTC of 1.98 seconds with ADAS compared to 1.79 seconds without ADAS. In crash avoidance scenarios, a longer minimum TTC is generally considered to be a safer driving performance as it provides drivers with more time to react (Shahini et al., 2022b). A longer minimum TTC with ADAS indicates that the drivers had more time to perceive the danger, make a decision, and execute an evasive maneuver. This highlights the advantage of the FCW on driver's ability to perceive and react to dangerous conditions quickly and effectively.

It was found that using both FCW and BSM led to an increase in the maximum longitudinal deceleration in scenarios where there was a braking lead vehicle and another vehicle in the driver's blind spot. This suggests that ADAS technologies can be particularly effective in high-risk driving situations where drivers need immediate and comprehensive information about surrounding vehicles to make safer decisions. It is important to note that a higher maximum longitudinal deceleration does not necessarily indicate safer driving performance alone, but when combined with other results such as minimum TTC, it supports the notion that a combination of FCW and BSM can assist drivers in making better decisions and executing safer maneuvers in crash avoidance scenarios.

Additionally, the results suggested that when FCW was active, drivers exhibited a larger maximum lateral acceleration, indicating faster and safer passing maneuvers, especially when combined with a larger minimum TTC as compared to when a combination of FCW and BSM was active. However, in BSM/FCW scenarios where both blind spot and lead vehicles were present, it was not always possible for drivers to switch lanes instantly as shown by the maximum lateral acceleration. Nevertheless, the use of ADAS technologies still improved their driving performance in BSM/FCW scenarios, as indicated by a larger maximum longitudinal deceleration. Therefore, the findings suggest that ADAS technologies such as FCW and BSM can aid officers in having safer passing maneuvers by providing timely information about their surroundings, as shown by shorter minimum TTC, larger maximum longitudinal deceleration, and maximum lateral acceleration depending on the situation.

Previous studies found that the use of ADAS technologies such as FCW may increase drivers' workload. However, this increase in workload can lead to longer time headway indicating improved collision avoidance performance (Chai et al., 2022). This finding is consistent with the Yerkes and Dodson (1908) which posits that moderate levels of arousal or workload can lead to improved performance, while low and high levels can lead to poorer performance. It is important to note that while ADAS warnings can increase drivers' workload, the Yerkes-Dodson Law suggests that this increased workload can lead to improved performance, as demonstrated by our findings. Therefore, the use of ADAS technologies such as FCW can be a valuable tool for improving driving performance and enhancing road safety, particularly in high-risk driving scenarios.

In general, the results suggested that ADAS primarily influenced the longitudinal aspect of driving performance, demonstrating the effectiveness of FCW and AEB in enhancing safe driving. However, the impact of BSM was limited, possibly due to its low salience. The limitations of the BSM system in this study may have been influenced by the visual-only warning icon and lack of auditory warning signal if officers did not turn their blinker on. The visual-only warning icon may have added to the primarily visually demanding driving task and led to an unnecessary visual load on the drivers (Wickens, 2008). As drivers must constantly monitor and integrate information from multiple sources, including the rearview mirrors, side mirrors, and the warning indicators, the additional cognitive demands imposed by the BSM system could have interfered with the drivers' ability to respond to the braking lead vehicle in a timely and effective manner. The absence of an auditory warning signal, except when the drivers turned on their blinkers, may have reduced the salience and effectiveness of the BSM warning. As most participants did not use their blinkers, this further diminished the salience of the BSM warning. This lack of salience may have led to drivers overlooking or not responding to the warning signal, which could have potentially been hazardous.

Therefore, there is a need to improve the design of BSM warnings for LEOs to make them more noticeable. Incorporating an auditory warning signal, improving the salience of the visual warning icon, and reducing the additional cognitive demands imposed by the system could lead to a more effective BSM system. By doing so, the system can better support drivers in avoiding potential collisions, especially in complex driving situations.

Although Hypothesis 2, which posited that officers would experience higher workload levels with ADAS on when dealing with critical incidents, was not supported by the results, the data indicated that officers exhibited a larger average PCPS (M=0.19) and a higher average blink rate (M=0.19) with ADAS as compared to driving without it (M=0.17 and M=0.16, respectively). While physiological measures indicated an overall higher average cognitive workload when negotiating a hazard, there was no significant increase in workload. This suggests that, when combined with the positive effects of ADAS on driving performance measures, ADAS warnings can increase drivers' workload up to an optimum point that enhances their performance, without imposing excessive cognitive load that would deteriorate their performance. These findings are in line with the Yerkes-Dodson Law, which posits that there is an inverted U-shaped relationship between arousal and performance. According to this principle, performance increases with physiological or mental arousal, but only up to a certain point. Beyond that point, further arousal becomes detrimental to performance (Yerkes & Dodson, 1908).

Regarding the DALI score, it was found that officers reported a lower level of workload with BSM and FCW/AEB system on in normal driving situation as compared to driving without ADAS. This finding is consistent with the results of maximum longitudinal acceleration, which suggested that drivers exhibited a larger maximum longitudinal deceleration with ADAS in similar scenarios. However, it was observed that there was no significant difference in DALI score between driving with and without ADAS during pursuit driving. Wicken's multiple resource theory can explain this finding as ADAS warnings require both auditory and visual resources, whereas pursuit driving demands high vigilance and the use of sirens and audio (Wickens, 2008). Per Wicken's theory, these two tasks may compete for the same resources and can overload drivers' memory load, resulting in no significant difference in DALI score between manual driving and driving with ADAS. In other words, the use of ADAS may not have a significant impact on workload perception during pursuit driving, as the task itself already requires a high level of cognitive resources. Therefore, it can be concluded that the effectiveness of ADAS may vary depending on the driving scenario and the cognitive demands imposed on the driver.

Hypothesis 3 stated that officers would have a higher trust in vehicle during the crash situation if the ADAS is in use. This hypothesis was supported by our results. This finding suggests that the use of ADAS can increase drivers' confidence in the safety of the vehicle and its ability to prevent or mitigate the impact of collisions. Increased trust in the vehicle is an important factor that can influence drivers' behavior and decision-making while driving. When drivers have greater trust in the safety features of their vehicle, they may be more likely to rely on these features to prevent collisions, which can lead to safer driving behavior overall (Shahini et al., 2022a). However, it is worth mentioning that real-world driving might be different than simulator driving especially in near crash scenarios. Officers' knowledge of the ADAS technology is a significant factor that determines their trust in the ADAS (DeGuzman & Donmez, 2021), and their intention to use the technology (Shahini et al., 2022a). Although we trained the officers with our driving simulator and video training before the experiment, the situation might be different in real-world driving. Officers may need extensive training to rely on ADAS in real-world driving situations. This training can be conducted in a controlled environment, and can include classroom instruction as well as hands-on driving exercises.

It was expected that pursuit driving would lead to a decrease in driving performance compared to normal driving conditions (H4), and the results confirmed this hypothesis. The results of the study suggested that the pursuit driving condition resulted in a larger maximum lateral acceleration and maximum longitudinal deceleration compared to normal driving conditions. Furthermore, it was found that the minimum time to collision and the time to change lanes were shorter in pursuit driving situations.

The process of passing another vehicle on the road requires several cognitive steps, including perception, decision-making, planning, execution, monitoring, and evaluation. The driver must identify the position, speed, and direction of travel of the other vehicle, assess whether it is safe to pass, plan the best trajectory and speed, execute the pass by steering the vehicle into the passing lane and maintaining control, continuously monitor the road and other vehicle, and finally evaluate the outcome of the pass and adjust their driving accordingly. These steps are crucial for a safe and successful passing maneuver (Kim et al., 2015).

Driving in the pursuit situation requires police officers to drive at high speeds, switch lanes quickly, and make sudden movements. Despite having the same initial headway time in both normal and pursuit driving conditions (2.5 seconds) in our experiment, pursuit driving presented a more pressing situation due to its high speed, negatively impacting most stages of passing maneuvers. This urgency results in shorter time for officers to accurately perceive the situation and plan the maneuver. However, the brake reaction time between manual and pursuit driving was not significantly different. To make up for the long brake reaction time in pursuit situation (i.e., not significantly different from normal driving situation), officers tended to take faster actions with the steering wheel, resulting in a quicker lane change time. Additionally, it led officers to make more abrupt passes, as demonstrated by larger maximum lateral and longitudinal decelerations. Consequently, the execution step was negatively impacted, as indicated by the shorter minimum TTC in pursuit driving, indicating a less safe passing maneuver.

Furthermore, the increased focus on the pursuit can cause the officer to allocate less attention to passing the lead vehicle, reducing their ability to safely execute the maneuver. These findings highlight the importance of designing driving assistance systems that can help officers maintain situational awareness and support them in executing safe passing maneuvers, especially during high-demand driving situations such as pursuit driving.

Hypothesis 5 stated that pursuit driving would lead to an increase in officers' workload compared to normal driving conditions. Results from PCPS, blink rate, and DALI supported this hypothesis; however, results from RMSSD did not reveal any significant effect of pursuit situation on officers' workload.

Previous research has indicated that blink rate is an effective and trustworthy measure of both cognitive and visual workload. It has been observed that cognitive tasks tend to increase blink rate, while visual tasks tend to inhibit it (Recarte et al., 2008b). Although driving itself is primarily a visually demanding activity, pursuit driving imposes additional demands such as the need to maintain a high speed, make quick decisions to execute safe passing maneuvers, evaluate the speed and situation of the lead vehicle, and process auditory information from the siren. These additional demands contribute to a high mental workload, which is reflected in the higher blink rate observed during pursuit driving situations. Thus, in pursuit driving situations, the high mental workload may have outweighed the visual demand of driving, resulting in an increased blink rate.

Based on Recarte and Nunes (2000), changes in mental workload during driving can be detected through changes in pupil size, even when factoring in variables such as daylight and natural road conditions. Previous studies have also found that pupil dilation can be observed in anticipation of complex driving maneuvers such as overtaking or approaching a roundabout, indicating increased mental workload during mental planning of maneuvers (Recarte et al., 2008b). In line with these findings, the present study found that pursuit driving situations resulted in a higher PCPS, indicating an increased cognitive load in these situations. Factors such as high-speed driving, urgency of the maneuver, siren sounds, and the focus on the fleeing vehicle all contributed to the higher workload in pursuit driving.

The use of subjective questionnaires was not effective in measuring the workload experienced by officers during short data blocks due to the subjective nature and recall biases associated with such questionnaires (Shahini et al., 2021). However, the DALI score findings were consistent with the results obtained from physiological measures in terms of the effects of pursuit situation on officers' workload level. The DALI questionnaire is designed to evaluate various aspects of driver workload, including task demand, task stress, situational stress, and environmental stress (Pauzié, 2008). The pursuit driving scenario not only increased the mental demand during the short durations of passing maneuver as measured by physiological responses, but also increased officers' overall perceived demand throughout the scenario as measured by DALI.

The results of the study did not support Hypothesis 5 in terms of RMSSD. One possible reason for this could be the limitation of the Kubios HRV Standard software used to analyze the RMSSD within the data blocks. The software has a minimum time duration of 30 seconds. Previous studies have suggested that shortening the analysis windows for RMSSD from 4 to 2 minutes is acceptable, while using 1-minute windows may lead to poor results (Bourdillon et al., 2017). In our study, the data blocks ranged mainly from 10-20 seconds, and increasing the analysis window to 30 seconds may decrease the sensitivity of the data blocks and affect the accuracy of measuring officers' workload during the data block. In summary, the limitation of the analysis software and the short duration of the data blocks used in the study may have contributed to the lack of support for Hypothesis 5 in terms of RMSSD.

The results did not support Hypothesis 6 as it was found that NDRT had no significant impact on driving performance. This finding are different from the results of Zahabi et al. (2021a), which found that officers experienced larger lane and speed deviations while engaged in an MCT task. However, Zahabi et al. (2021) did not evaluate the officers' performance in crash scenarios. It is possible that in such situations, officers are more focused on driving to prevent crashes, as they were informed that their main task was to drive and not perform NDRT. Moreover, the initial headway was set at 2.5 seconds, and upon reviewing the videos, it was observed that most participants completed NDRT after passing the hazard or stopped behind the lead vehicle and completed NDRT after applying the brakes.

Previous research found that the use of in-vehicle technologies can have a negative impact on drivers' driving performance (Shahini et al., 2022b; Zhang & Kaber, 2016). It is worth noting that the officers who participated in this study were highly skilled drivers who frequently engage in patrols, and they were only required to perform a plate number check task while using the MCT without any other interaction. Other studies that suggested distractions negatively affect driving performance have used complex visual and cognitive secondary tasks during driving simulations. In patrol situations, officers may have to respond to emergency calls or use the radio, which could increase the demands on their attention and potentially affect their driving performance while using the MCT. The findings of this study were consistent with those of (Zahabi & Kaber, 2018a), which found that the use of MCT did not have a significant impact on police officers' driving performance as measured by lane deviation, speed deviation, and brake reaction time in the presence of hazards such as vehicle and pedestrian obstructions. It is important to note that these experiments were conducted in a controlled environment, and the officers were made aware of the importance of protecting the driving task and their safety and were informed that using the on-board computer might be distracting at the beginning of the experiment.

Hypothesis 7 suggested that when faced with critical incidents, drivers would experience a lower workload when they are not engaged in a non-driving related task as compared to when they are performing such a task. The results of this hypothesis were supported by the blink rate and PCPS measures. The findings from blink rate and PCPS indicated that officers had a significantly higher cognitive load when engaged in non-driving related tasks as compared to driving without such tasks. In contrast, RMSSD results did not reveal any significant effect of NDRT.

Blink rate has been found to be an indicator of both visual and cognitive demand (Holland & Tarlow, 1972; Recarte et al., 2008a). Specifically, a decrease in blink rate has been associated with increased visual demand, while an increase in blink rate has been linked to increased cognitive demand (Recarte et al., 2008b). The task in this study required participants to engage in various activities that required visual, cognitive, auditory, verbal, and motor demands. Due to the high level of mental strain involved in the task, participants experienced a higher cognitive load, which was indicated by a higher rate of blinking. Participants were required to listen to audio instructions, perceive the question, switch among pages, find the correct answer, and vocalize their response. This complex and demanding task likely required significant cognitive resources, which may have resulted in the observed increase in blink rate and PCPS.

In contrast, the RMSSD results did not reveal any significant effect of NDRT. This result may suggest the measurement of RMSSD may not be sensitive enough to capture changes in cognitive load associated with NDRTs in short durations of time.

The DALI score was not used in evaluating the effects of NDRT on workload because it was distributed at the end of the experiment, whereas the on/off manipulation of non-driving related tasks was done within each scenario.

3.4.2. Brake reaction time model

The second objective of this study was to develop a model that could predict police officers' brake reaction time during critical driving situations such as a braking lead vehicle. Although inferential statistics did not reveal significant effects of pursuit driving or NDRT on brake reaction time, the brake reaction model revealed that adding additional parameters (ρ=-0.1, η=-0.1, and γ=-0.1) could improve the basic model, as evidenced by a smaller RMSE. The inclusion of these parameters led to longer estimated brake reaction times when officers were under a higher cognitive load, whether due to pursuit driving, NDRT, or the interaction between the two. This finding is consistent with the cognitive control hypothesis, which posits that tasks requiring cognitive control are more affected by cognitive load than tasks that have become automatized through practice. Previous research suggested that object and event detection (OED) performance is impaired by cognitive load in tasks that rely on cognitive control, such as detection response tasks (DRT), which involve responding to visual or tactile stimuli presented at intervals of 3 to 5 seconds. DRT is typically not extensively practiced and is therefore sensitive to interference from secondary tasks that require cognitive control. Studies have reported that cognitively loading tasks increase DRT response times compared to a baseline (no-task) condition. Similarly, many studies have found that cognitive load increases brake response time or accelerator pedal release time relative to a no-task condition (Engström et al., 2017). In this study, because the brake situations (i.e., a lead vehicle suddenly braking) were unexpected and therefore unlikely to become automatized even for experienced officers, it is reasonable to expect longer brake reaction times under higher cognitive load due to pursuit driving and NDRT. The inferential statistics (PCPS and blink rate data) also suggest that pursuit driving and NDRT increased officers' cognitive load, further supporting the model results based on the cognitive control theory.

The results of this model can be used as an input for an adaptive FCW system per officers' request in a survey study by Wozniak et al. (2021). The critical warning distance R_W can be expressed as the following equation (Nakaoka et al., 2008):

$$R_w = \tau_r V + \frac{V^2}{2a} - \frac{V_p^2}{2a_p} + R_{stop} \quad \text{Equation 3.8}$$

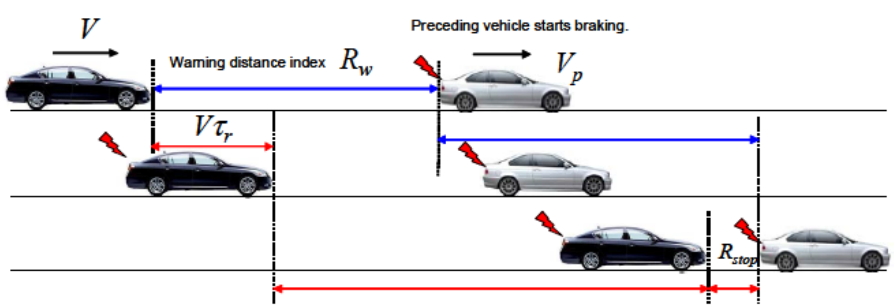

Figure 3.28. Description of warning distance index reprinted from Nakaoka et al. (2008)

Where, τ_r indicates the braking reaction time of driver, V , the following vehicle speed, V_p the preceding vehicle speed, a the host vehicle longitudinal deceleration, a_p the preceding vehicle longitudinal deceleration, R_{stop} the relative distance margin when both vehicles stop. Here, τ_r indicates the braking reaction time of driver. From the above expression, if $R > R_W$, no assistance is applied. On the other hand, if, the $R \ll R_W$, warning sound device will be activated.

To implement an adaptive FCW system based on the model's predictions of brake reaction time, the police vehicle would need to be equipped with various sensors and devices. Firstly, a speed sensor or speedometer in the police vehicle would be required to measure the following vehicle speed (V). Additionally, radar or camera sensors that can detect the speed of the vehicle ahead would be necessary to obtain the preceding vehicle speed (V_p). The host vehicle longitudinal deceleration (a) can be measured using the vehicle's braking system or an accelerometer. Similarly, the deceleration rate of the vehicle ahead (a_p) can be estimated using the same sensors that provide the preceding vehicle speed. The model's prediction of the braking reaction time of the driver (τ_r) is also essential information required for the adaptive FCW system provided by this study. Finally, the relative distance margin when both vehicles stop (R_{stop}) can be obtained by measuring the length of the police vehicle and the distance between the police vehicle and the vehicle ahead when both vehicles come to a stop. With this information, the critical warning distance (R_w) can be calculated using the equation provided above. If the actual relative distance (R) between the police vehicle and the vehicle ahead is less than R_w, the warning sound device should be activated to alert the driver of the police vehicle. If R is greater than R_w, no assistance is needed. Therefore, a speed sensor, radar or camera sensors, an accelerometer, and a warning sound device would be necessary to implement an adaptive FCW system and effectively use the model's predictions of brake reaction time as the input for an adaptive FCW.

3.4.3. Steering avoidance model

The third objective of this study was to build a model to predict officers' steering wheel angle when driving with BSM and trying to change their lane when there is a vehicle in their blind spot. Results from the steering avoidance model suggested that $k = 16$, $T_H = 0.6$, and $T_A = 7$ result in the optimal model as calculated by the smallest RMSE. Although the RMSE for the model is too small (0.023), the R^2 of the model is relatively small suggesting that the model can only explain 67% of the variation in data. This observation could be due to the short duration of the data collection periods, since the data block in this analysis starts from the moment that leading vehicle brakes and ends when the driver notices the vehicle in their blind spot and brakes. As shown in Figure 3.27, the officers' steering behavior is not always predictable in critical situations specifically when there is a vehicle in their blind spot. The figures illustrated that not always officers rotate the steering wheel to a certain degree, wait for the vehicle in blind spot to pass, and then continue rotating the steering wheel. Instead, they sometimes quickly rotate the steering wheel to change their lane and rotate it back when seeing a vehicle in their blind spot. While this model can be useful in situation where officers demonstrate a predictable steering behavior (i.e., rotating the steering wheel to a certain position, waiting for the lead vehicle to pass, and then continuing to rotate the steering wheel), it might not be as useful in unpredictable situations where we see reverse steering wheel rotation due to the vehicle in blind spot. Further research is warranted to explore whether incorporating additional parameters into the model could enhance its accuracy in scenarios where drivers rotate the steering wheel to switch lanes and then rotate it back to prevent accidents when a vehicle is present in their blind spot. Investigating these aspects has the potential to improve the model's performance and provide a more comprehensive understanding of such driving maneuvers.

3.5. Conclusion

The study investigated the effects of ADAS on police officers' performance, workload, and trust in critical driving situations (e.g., a braking lead vehicle) in a driving simulation study. The findings suggested that ADAS primarily influenced the longitudinal aspect of driving performance, demonstrating the effectiveness of FCW and AEB in enhancing safe driving. However, the impact of BSM was limited, possibly due to its low salience. The study also found that ADAS warnings can increase drivers' workload up to an optimum point that enhances their passing performance. There is a need to improve the design of BSM warnings for LEOs to make them more noticeable, incorporating an auditory warning signal, improving the salience of the visual warning icon, and reducing the additional cognitive demands imposed by the system. Overall, the study suggests that ADAS technologies such as FCW and BSM can aid officers in having safer passing maneuvers by providing timely information about their surroundings, as shown by shorter minimum TTC, larger maximum longitudinal deceleration, and maximum lateral acceleration depending on the situation.

The results also suggested that police officers had more confidence in the safety of their vehicle when ADAS was employed, which resulted in safer driving behavior. However, during pursuit situations, officers' driving performance worsened, and their cognitive load increased, emphasizing the necessity of developing ADAS that can help drivers maintain situational awareness in high-demand driving conditions. Additionally, the study found that while the NDRT increased officers' cognitive load, it did not affect their performance, probably because officers are adept at multitasking and are well-trained on the driving task.

The second aim of the research was to create predictive models to estimate police officers' brake reaction time during critical driving scenarios when a lead vehicle is braking and their steering wheel angle while driving with BSM and attempting to change lanes when there is a car in their blind spot. Adding extra parameters to the brake reaction model to indicate cognitive load due to pursuit driving and NDRT improved the model, and led to a longer estimated brake reaction time. The results of the model can be used as input for an adaptive FCW system, but to implement the system, various sensors and devices, such as speed sensors, radar or cameras, and a warning sound device, would be required. The study also found that the steering avoidance model was not always reliable in critical situations when there is a car in the officer's blind spot, and that the model could only account for 67% of the variation in data.

In addition to its implications for police officers, this study has potential benefits for civilian drivers as well. The findings regarding the effectiveness of ADAS technologies like FCW and AEB in enhancing safe driving and improving longitudinal driving performance can be directly applicable to civilian vehicles. By implementing these ADAS features, civilian drivers can experience increased safety on the roads by receiving timely warnings and assistance to avoid potential collisions. Furthermore, the study's insights on workload optimization and the need to improve the design of BSM warnings can also be translated into civilian vehicles, allowing drivers to handle critical driving situations more effectively and be alerted to vehicles in their blind spots with improved salience and reduced cognitive demands. Overall, the study's findings and recommendations provide valuable guidance for the development and implementation of ADAS technologies that can benefit civilian drivers, enhancing their driving performance, safety, and confidence on the road.

3.6. Limitations

One limitation of this study is that some participants experienced simulation sickness and could not complete the experiment. Moreover, all participants were recruited from Texas. Additionally, the study only included male participants, and gender distribution was not balanced, which could have biased the results.

Furthermore, one officer mentioned that police cars typically drive in the left lane, even when not pursuing someone, whereas in this study, officers were asked to drive in the right lane if not pursuing due to the limitations of the driving simulator software. This deviation from real-world driving practices could have affected the study's results. Additionally, the study was conducted during the day, and the findings may not be generalizable to nighttime driving.

While the brake reaction time model used in the study had a high level of accuracy, as measured by the RMSE, it may not be applicable to naturalistic police driving situations, where there may be differences between simulator and real-world driving situations. Moreover, officers are typically required to engage in multiple

NDRTs while driving (e.g., using radio, cell phone, MCT), whereas in this study, only one NDRT was present.

Furthermore, the RMSSD results did not reveal any significant effect of study manipulations, mostly due to the short duration of the data blocks. Finally, the BSM warning system in the study was a visual warning, and it only produced an auditory warning if officers turned their blinkers on. Although the design was based on existing BSM warnings in police cars, many officers did not turn on their blinkers when negotiating hazards, which reduced the effectiveness of the BSM as the icon may not have been noticed by the officers. To address these limitations, future studies could recruit participants from different states and genders to achieve more generalizable results. Additionally, studies could use a driving simulator that more closely replicates naturalistic driving situations to provide a better representation of real-world driving behavior. Finally, BSM warning systems could be designed to be more effective by incorporating auditory warnings, even when officers do not use their blinkers.

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APPENDIX A

DRIVING ACTIVITY LOAD INDEX (DALI)

During the test you have just completed you may have experienced some difficulties and constraints with regard to driving task.

You will be asked to evaluate this experience with regard to 6 factors, which are described below. Please read each factor and its description carefully and ask the experimenter to explain anything you do not fully understand.

Title	**Endpoints**	**Description**
Effort of attention	Low/high	To evaluate the attention required by the activity- to think about, to decide, to choose, to look for and so on
Visual demand	Low/high	To evaluate the visual demand necessary for the activity
Auditory demand	Low/high	To evaluate the auditory demand necessary for the activity
Temporal demand	Low/high	To evaluate the specific constraint owing to timing demand when running the activity
Interference	Low/high	To evaluate the possible disturbance when running the driving activity simultaneously with any other supplementary task such as phoning, using systems or radio and so on
Situational stress	Low/high	To evaluate the level of constraints/stress while conducting the activity such as fatigue, insecure feeling, irritation, discouragement and so on

For each of the pairs below, circle the scale title that represents the more important contributor to workload when you are performing the driving task.

Effort of attention	or	Visual demand
Effort of attention	or	Auditory demand
Effort of attention	or	Temporal demand
Effort of attention	or	Interference
Effort of attention	or	situational stress
Visual demand	or	auditory demand
Visual demand	or	Temporal demand
Visual demand	or	Interference
Visual demand	or	Situational stress
Auditory demand	or	temporal demand
Auditory demand	or	Interference
Auditory demand	or	situational stress
Temporal demand	or	Interference
Temporal demand	or	situational stress
Interference	or	Situational stress

For each factor you will be required to rate the level of constraint felt during the test on a scale from 0 (very low level of constraint) to 5 (very high level of constraint), with regard to the driving task.

Global attention demand:

Think about the mental (i.e. to think about, to decide…), visual and auditory demand required during the test to perform the whole activity.

Low					High
0	1	2	3	4	5
☐	☐	☐	☐	☐	☐

Visual demand:

Think about the visual demand required during the test to perform the whole activity.

Low					High
0	1	2	3	4	5
☐	☐	☐	☐	☐	☐

Auditory demand:

Think about the auditory demand required during the test to perform the whole activity.

Low					High
0	1	2	3	4	5
☐	☐	☐	☐	☐	☐

Stress:

Think about the level of stress (i.e. fatigue, insecurity, irritation, feelings of discouragement) during the whole activity.

Low High

0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Temporal demand:

Think about the specific constraints felt due to time pressure of completing tasks during the whole activity.

Low High

0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Interference:

Think about the disturbance to the driving task when completing supplementary tasks (i.e. via the in-vehicle information system) simultaneously.

Low High

0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

APPENDIX B

TRUST QUESTIONNAIRE

Trust: Performance	I trust the system to safely operate in the next drive	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	The system provides safety	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	The system is dangerous	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	The system's performance matches my expectations	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	The system is trustworthy	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	I trust the system's performance	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
Trust: Process	The system's mode of operation is obscure	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	The system is deceptive	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	The system's mode of operation leads to unfavorable or dangerous outcomes	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	I am familiar with the system	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	I suppose the system works accurately	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	I trust the system's mode of operation when the lead vehicle brakes	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
Trust: Purpose	The system is a reliable partner	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree

APPENDIX B

TRUST QUESTIONNAIRE CONTINUED

Trust: Purpose	The system's communications decrease uncertainty related to the systems intention	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	Driving task responsibility was explicitly clarified	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	I am convinced of the system	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree
	I mistrust the system's purpose	Entirely Disagree	Mostly Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Mostly Agree	Entirely Agree

Note: It is crucial to clarify that officers were requested to assess their confidence in the overall safety of the vehicle, rather than specifically evaluating the functionality, failure, or activation of the Advanced Driver Assistance Systems (ADAS). In the questionnaire, participants were instructed to interpret the term "system" as referring to the vehicle itself, rather than solely focusing on the ADAS.

APPENDIX C

BRAKE REACTION TIME MODEL

```
#Uncomment to install packages

#install.packages(c("tidyverse","data.table","gganimate","rust", "writexl", "readxl",
"dplyr", "lubridate"))

#install.packages("tidyverse")

#install.packages("gganimate")

#install.packages("readxl")

#install.packages("writexl")

library(tidyverse)

library(data.table)

library(readxl)

library(writexl)

library(dplyr)

library(lubridate)

extract_block_times <- function(file_path) {

  # Read the excel file

  data_file <- read_excel(file_path)

  # Extract start and end times for blocks with data block values of 1 and 2

  block_starts <- data_file$MediaTime[data_file$User2 == 1 &
dplyr::lead(data_file$User2) == 2]

  block_ends <- data_file$MediaTime[data_file$User2 == 2 &
dplyr::lead(data_file$User2) == 0]

  # Calculate the duration of each block

  block_durations <- block_ends - block_starts

  # Create a new column Block, based on the User2 values

  block_num <- ifelse(data_file$User2 == 0, 0,

                  ifelse(data_file$MediaTime < block_starts[2], 1, 2))
```

```
  # Extract the time when Brake>=1.81 and User11==5 for the first time in each block where shows the subject and lead vehicle's brake time
  lead_vehicle_brake_times <- numeric(length(block_starts))
  brake_times <- numeric(length(block_starts))
for (i in seq_along(block_starts)) {
    block_start_idx <- which(data_file$MediaTime >= block_starts[i] & data_file$MediaTime < block_ends[i])
    brake_idx <- which(data_file$Brake[block_start_idx] >= 1.81)[1]
    lead_vehicle_brake_idx <- which(data_file$User11[block_start_idx] <= 5)[1]
    if (!is.na(brake_idx)) {
      brake_times[i] <- data_file$MediaTime[block_start_idx][brake_idx]
    }
    if (!is.na(lead_vehicle_brake_idx)) {
      lead_vehicle_brake_times[i] <- data_file$MediaTime[block_start_idx][lead_vehicle_brake_idx]
    }
  }
  # Calculate the actual brake reaction time for each block
  brake_reaction_times <- brake_times - lead_vehicle_brake_times
  # Return the start and end times, duration, and brake times for each block
  return(data.frame(Block = 1:length(block_starts),
                    Start_Time = block_starts,
                    End_Time = block_ends,
                    Duration = block_durations,
                    Brake_Time = brake_times,
                    Lead_Vehicle_Brake_Time = lead_vehicle_brake_times,
                    Brake_Reaction_Time = brake_reaction_times))
}
```

```
# Define the path to the directory containing the Excel files
dir_path <- "//coe-fs.engr.tamu.edu/Grads/farzane97/Desktop/Tamu/Safe_D/Driving sim/Brake/"


# Get a list of all Excel files in the directory
file_names <- list.files(path = dir_path, pattern = "*.xlsx", full.names = TRUE)


# Apply the function to all Excel files using lapply()
block_times_list <- lapply(file_names, extract_block_times)


# Combine the results into a single data frame
block_times <- do.call(rbind, block_times_list)


# Print the results
print(block_times)
block_times_list


#Extracting each block from excel files and convert them to a single excel file
# Define the path to the directory containing the Excel files
dir_path <- "//coe-fs.engr.tamu.edu/Grads/farzane97/Desktop/Tamu/Safe_D/Driving sim/Brake/"
# Define the path to the directory where the output files will be saved
output_dir_path <- "//coe-fs.engr.tamu.edu/Grads/farzane97/Desktop/Tamu/Safe_D/Driving sim/Brake/Blocks/"
# Get a list of all Excel files in the directory
file_names <- list.files(path = dir_path, pattern = "*.xlsx", full.names = TRUE)
```

```
# Loop through each file and extract each block as a new Excel file
for (file_path in file_names) {
  # Read the excel file
  data_file <- read_excel(file_path)

  # Extract start and end times for blocks with data block values of 1 and 2
  block_starts <- data_file$MediaTime[data_file$User2 == 1 &
dplyr::lead(data_file$User2) == 2]
  block_ends <- data_file$MediaTime[data_file$User2 == 2 &
dplyr::lead(data_file$User2) == 0]

  # Loop through each block and extract the data
  for (i in seq_along(block_starts)) {
    # Create a new file name based on the original file name and block number
    block_num <- i
    file_name <- gsub(".xlsx", "", basename(file_path))
    new_file_name <- paste0(file_name, "_Block", block_num, ".xlsx")
    new_file_path <- file.path(output_dir_path, new_file_name)

    # Extract the data for this block
    block_start <- block_starts[i]
    block_end <- block_ends[i]
    block_data <- data_file[data_file$MediaTime >= block_start &
data_file$MediaTime <= block_end, ]

    # Write the data to a new Excel file
    write_xlsx(block_data, new_file_path)
  }
```

```
# Define the function to calculate evidence accumulation
calculate_evidence_accumulation <- function(file, Beta, etta, int, m, l, P, ST, dt, j) {
  # Define Looming
  file$Looming <- 1/file$User9
  # Set the first Evidence_accumulation to the initial value of Evidence_accumulation
  file$Evidence_accumulation[1] <- 0
  # Find the row number where User11 value is equal to 5 for the first time which is
when the lead vehicle brakes
  row_num_start <- which(file$User11 <= 5)[1]
  # Calculate Evidence_accumulation for each row after the starting row using the
formula
  for (i in row_num_start:nrow(file)) {
    file$Evidence_accumulation[i] <- file$Evidence_accumulation[i-1] +
      ((j) * (file$Looming[i])*(1+(Beta*ST)+(etta*P)+(int*P*ST)) + (m) +
rnorm(n=1,mean = 0,sd = l))*dt
  }
  # Find the first row where the absolute value of Evidence_accumulation is >= 1
  row_num_end <- which(abs(file$Evidence_accumulation) >= 1)[1]
  # Get the MediaTime value associated with that row
  media_time <- file$MediaTime[row_num_end]


  # Calculate the lead vehicle brake time
  lead_vehicle_brake_time <- file$MediaTime[which(file$User11 <= 5)[1]]
  # Calculate the predicted brake reaction time
  predicted_brake_reaction_time <- media_time-lead_vehicle_brake_time
  # Return the updated file with the Evidence_accumulation column, the MediaTime
value, the lead vehicle brake time, and the predicted brake reaction time
  return(list(file, media_time, lead_vehicle_brake_time,
predicted_brake_reaction_time))
```

```
}

#Create a results table that show the actual brake reaction time and predicted brake reaction time for each file with given parameters

# Create an empty results table

results_tbl <- data.frame(file_name = character(),

                          media_time = double(),

                          lead_vehicle_brake_time = double(),

                          predicted_brake_reaction_time = double(),

                          actual_brake_reaction_time = double(),

                          diff_brake_reaction_time = double())

# Loop through the files and calculate Evidence_accumulation, lead vehicle brake time, and predicted brake reaction time for each one

for (file_name in file_names) {

  # Read the Excel file

  file <- read_excel(file_name)

  P=file$User1[1]

  ST=file$User1[2]

  # Calculate the Evidence_accumulation, lead vehicle brake time, and predicted brake reaction time using the function

  results <- calculate_evidence_accumulation(file, Beta = -0.2, etta = -0.2, int=-0.2, m = -3, l = 3, dt = 0.01, P=P, ST=ST, j=5)

  # Get the updated file, the MediaTime value, the lead vehicle brake time, and the predicted brake reaction time

  updated_file <- results[[1]]

  media_time <- results[[2]]

  lead_vehicle_brake_time <- results[[3]]

  predicted_brake_reaction_time <- results[[4]]

  # Calculate the actual brake reaction time

  brake_start_time <- min(updated_file$MediaTime[which(updated_file$User11 <= 5)])
```

```
  # Find the first time the lead vehicle brakes

  brake_end_time <- min(updated_file$MediaTime[which(updated_file$Brake >= 1.81
& updated_file$User11 <= 5)])

  # Find the time when the driver starts braking

  actual_brake_reaction_time <- (brake_end_time - brake_start_time) # Calculate the
time difference in seconds


  # Calculate the difference between the predicted and actual brake reaction times

  diff_brake_reaction_time <- predicted_brake_reaction_time -
actual_brake_reaction_time


  # Add the results to the table

  results_tbl <- rbind(results_tbl, data.frame(file_name = file_name,

                                               media_time = media_time,

                                               lead_vehicle_brake_time = lead_vehicle_brake_time,

                                               predicted_brake_reaction_time =
predicted_brake_reaction_time,

                                               actual_brake_reaction_time =
actual_brake_reaction_time,

                                               diff_brake_reaction_time = diff_brake_reaction_time))

}

# Print the results table

print(results_tbl)


#Find the optimized j and Beta and etta and m and l values based on the smallest
difference—measured by a two sample Kolmogorov–
Smirnov (KS)—between the observed braking reaction times and predicted reaction
times
# Define the path to the directory containing the Excel files

dir_path <- "//coe-fs.engr.tamu.edu/Grads/farzane97/Desktop/Tamu/Safe_D/Driving
sim/Brake/Blocks/"
```

```
# Define the range of j and Beta and etta and m and l values to loop over
j_values <- seq(1, 8, by = 1)
beta_values <- seq(-0.5, 0.5, by = 0.05)
etta_values <- seq(-0.5, 0.5, by = 0.05)
m_values <- seq(-1, 1, by = 0.05)
l_values <- seq(0.1, 1, by =0.05)
int_values <- seq(-0.5, 0.5, by = 0.05)

# Define a function to calculate the relevant metrics for a given file, j, and Beta values
calculate_metrics <- function(file, j, beta, etta,int, m, l) {
  P=file$User1[1]
  ST=file$User1[2]
  # Calculate the evidence accumulation, lead vehicle brake time, and predicted brake reaction time using the function
  results <- calculate_evidence_accumulation(file, Beta = beta, etta = etta, int=int, m = m, l = l, dt = 0.01, P = P, ST = ST, j = j)

  # Check if there is a row where the absolute value of Evidence_accumulation is >= 1
  idx <- which(abs(results[[3]]) >= 1)[1]
  if (is.na(idx)) {
    # If there is no such row, return NULL
    return(NULL)
  }
  # Extract the updated file and the MediaTime value associated with the first row where the absolute value of Evidence_accumulation is >= 1
  updated_file <- results[[1]]
  media_time <- results[[2]]

  # Extract the lead vehicle brake time and the predicted brake reaction time
```

```
  lead_vehicle_brake_time <- file$MediaTime[which(file$User11 <= 5)[1]]
  predicted_brake_reaction_time <- media_time - lead_vehicle_brake_time

  # Extract the actual brake reaction time from the updated file
  brake_start_time <- min(updated_file$MediaTime[which(updated_file$User11 <=
5)])
  brake_end_time <- min(updated_file$MediaTime[which(updated_file$Brake >= 1.81
& updated_file$User11 <= 5)])
  actual_brake_reaction_time <- brake_end_time - brake_start_time

  # Calculate the difference between the predicted and actual brake reaction times
  diff_brake_reaction_time <- predicted_brake_reaction_time -
actual_brake_reaction_time

  # Return a named list of the relevant metrics
  list(
    Media_Time = media_time,
    Lead_Vehicle_Brake_Time = lead_vehicle_brake_time,
    Predicted_Brake_Reaction_Time = predicted_brake_reaction_time,
    Actual_Brake_Reaction_Time = actual_brake_reaction_time,
    Diff_Brake_Reaction_Time = diff_brake_reaction_time,
    Beta = beta
  )
}

# Initialize the minimum average difference in brake times to a large value
min_avg_diff <- Inf
# Initialize the optimal j, Beta, etta, int, m, and l values
optimal_values <- c(0, 0, 0, 0, 0,0)
```

```
# Create an empty list to store the metrics for all files
metrics_list <- list()

# Loop over all files
for (file_name in file_names) {
  file <- read_excel(file_name)

  for (j in j_values) {
    for (beta in beta_values) {
      for (etta in etta_values) {
        for (int in int_values){
        for (m in m_values) {
          for (l in l_values) {
            metrics <- calculate_metrics(file, j, beta, etta, int, m, l)
            if (is.null(metrics)) {
              next
            }

            # Calculate the absolute difference in brake times for this file, j, beta, etta, m,
and l value
            abs_diff <- (abs(metrics$Diff_Brake_Reaction_Time)^2)

            # Add the relevant metrics to the list
            metrics_list <- c(metrics_list, list(c(File_Name = file_name, J_Value = j,
Beta_Value = beta, Etta_Value = etta, Int_Value=int, M_Value = m, L_Value = l,
metrics)))
          }
        }
```

```
        }
      }
    }
  }
}
# Combine the list of metrics into a data frame
results_table <- do.call(rbind, lapply(metrics_list, as.data.frame))
colnames(results_table)
# Subset results_table to include relevant columns
results_subset <- results_table[, c("File_Name", "J_Value", "Beta_Value",
"Etta_Value", "Int_Value", "M_Value", "L_Value", "Actual_Brake_Reaction_Time",
"Predicted_Brake_Reaction_Time")]

# Calculate absolute difference between actual and predicted brake reaction times
results_subset$Abs_Diff <- abs(results_subset$Actual_Brake_Reaction_Time -
results_subset$Predicted_Brake_Reaction_Time)

# Calculate KS statistic for each combination of parameters
ks_stat <- apply(results_subset[, c("Abs_Diff")], 1, function(x) {
  ks.test(x, results_subset$Abs_Diff)$statistic
})

# Find index of minimum KS statistic
min_index <- which.min(ks_stat)
# Get combination of parameters corresponding to minimum KS statistic
best_params <- results_subset[min_index, c("File_Name", "J_Value", "Beta_Value",
"Etta_Value", "Int_Value", "M_Value", "L_Value")]
# Print the optimized parameters

Best_params
```

APPENDIX D

STEERING WHEEL ANGLE MODEL

```
#Load required libraries
library(readxl)
library(tidyverse)
library(openxlsx)

# create an empty vector to store the maximum values
max_values <- c()

# loop through the files in the "blocks" directory
for (file in list.files("blocks", pattern = "\\.xlsx$", full.names = TRUE)) {
  # read the Excel file into a data frame
  df <- read_excel(file)

  # calculate the maximum visual looming value and add it to the vector
  max_values <- c(max_values, max(1/df$User9))
}

# print the maximum value
cat("Maximum visual looming value:", max_values, "\n")

# create an empty vector to store the MediaTime values
media_times <- c()

# get list of Excel files in "blocks" directory
files <- list.files("blocks", pattern = "\\.xlsx$", full.names = TRUE)
```

```r
# initialize media_times variable
media_times <- numeric()

# loop through files
for (file in files) {
  # read Excel file into data frame
  df <- read_excel(file)

  # calculate the maximum steer value and its half value
  max_steer <- max(df$Steer, na.rm = TRUE)
  half_max_steer <- max_steer / 2

  # filter rows where Steer >= half of maximum steer
  filtered_df <- filter(df, Steer >= half_max_steer)

  # calculate the MediaTime when Steer first reaches half of maximum steer
  if (nrow(filtered_df) > 0) {
    media_time <- min(filtered_df$MediaTime) - df$MediaTime[1]
    media_times <- c(media_times, media_time)
  }
}

# print the MediaTime values
print(media_times)
```

```
# create an empty vector to store the Lead brake time values
Lead_brake_time <- c()

# loop through files
for (file in files) {
  # read Excel file into data frame
  df <- read_excel(file)

  # filter rows where User9 <= 5
  filtered_df <- filter(df, User9 <= 5)

  # find the first MediaTime where User9 <= 5
  if (nrow(filtered_df) > 0) {
    lead_brake_time <- min(filtered_df$MediaTime)
    Lead_brake_time <- c(Lead_brake_time, lead_brake_time)
  }
}

# print the Lead brake time values
print(Lead_brake_time)

calculate_steering_angle <- function(df, max_values, Lead_brake_time,media_times,
K, TA, TH) {
  # create a vector to store the steering wheel angles
  steering_angles <- numeric(nrow(df))

  # loop through the rows
  for (i in nrow(df)) {
```

```
    # calculate the steering wheel angle using the formula
    steering_angles[i] <- (K + 20) * max_values[df] * (2.71828^(-((df$MediaTime[i] -
Lead_brake_time[df]) - (media_times[df] + (-0.5 + 0.1 * TA)))^2 / (2 * TH * 0.1)))
  }

  return(steering_angles)
}



# define the range of K, TA, and TH
K_range <- 0:50
TA_range <- 1:10
TH_range <- seq(0.1, 1, by = 0.05)

# create an empty data frame to store the results
results_df <- data.frame(K = numeric(), TA = numeric(), TH = numeric(), RMSE =
numeric())

# loop through the range of K, TA, and TH
for (K in K_range) {
  for (TA in TA_range) {
    for (TH in TH_range) {

      # calculate the predicted steering wheel angle for each file and each row
      predicted_angles_list <- list()
      actual_angles_list <- list()
      for (file in files) {
        df <- read_excel(file)
```

```
    max_value <- max_values[[which(files == file)]]
    lead_brake_time <- Lead_brake_time[[which(files == file)]]
    media_time <- media_times[[which(files == file)]]
    predicted_angles <- numeric(nrow(df))
    actual_angles <- df$Steer
    for (i in 1:nrow(df)) {
      predicted_angles[i] <- (K + 20) * max_value * (2.71828^(-((df$MediaTime[i] - 
lead_brake_time) - (media_time + (-0.5 + 0.1 * TA)))^2 / (2 * TH * 0.1)))
    }
    predicted_angles_list[[file]] <- predicted_angles
    actual_angles_list[[file]] <- actual_angles
  }

  # calculate the RMSE of the predicted steering wheel angle for each file and each 
lane
  RMSE_list <- list()
  for (file in files) {
    predicted_angles <- predicted_angles_list[[file]]
    actual_angles <- actual_angles_list[[file]]
    RMSE <- sqrt(mean((predicted_angles - actual_angles)^2))
    RMSE_list[[file]] <- RMSE
  }
  overall_RMSE <- mean(unlist(RMSE_list))

  # add the results to the data frame
  results_df <- rbind(results_df, data.frame(K = K, TA = TA, TH = TH, RMSE = 
overall_RMSE))

}
```

```
  }
}

# find the optimal K, TA, and TH that minimize the RMSE
optimal_results <- results_df[which.min(results_df$RMSE), ]
optimal_K <- optimal_results$K
optimal_TA <- optimal_results$TA
optimal_TH <- optimal_results$TH
cat("Optimal values of K, TA, and TH:", optimal_K, optimal_TA, optimal_TH, "\n")

#Testing the results
K=15
TA=7
TH=0.6
# loop through files
for (file in files) {
  # read Excel file into data frame
  df <- read_excel(file)

  # calculate the steering wheel angle for each row
  steering_angles <- numeric(nrow(df))
  for (i in 1:nrow(df)) {
    steering_angles[i] <- (K) * max_values[[which(files == file)]] * (2.71828^(-
((df$MediaTime[i] - Lead_brake_time[[which(files == file)]]) -
(media_times[[which(files == file)]] + (-0.5 + 0.1 * TA)))^2 / (2 * TH * 0.1)))
  print (df$MediaTime[i])
    }
```