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Advanced Driver Assistance Systems and Emotion-Based Driver Behavior

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ABSTRACT

Although Advanced Driver Assistance Systems (ADAS) have helped reduce driving risk, the control of the vehicle is still largely in the hands of a human driver, whose emotional state while driving could have a significant impact on their risk, and is in constant flux. Emotions have been proven to affect the driving habits of drivers, although the valence, magnitude and significance of impact depend on the individual. Addressing driving risk with ADAS, therefore, should focus on adapting to adverse emotional states. In this paper, we review the current understanding of emotion state development and evolution in drivers and their impact on behavior. Secondly, we review the current capabilities in advanced driver assistance systems. This work is the first part of a broader research effort aimed at developing ADAS that are capable of adapting to driver emotion state.

Keywords: Emotion-based driving, Driver assistance, Risk, Human reliability

INTRODUCTION

Advanced Drivers Assistance Systems (ADAS) are still developing capabilities in the automotive industry. These systems, which include parking assistance, lane-keeping assistance, adaptive cruise control, and emergency braking, have helped reduce the number and/or severity of automobile collisions since their introduction. However, these systems have not completely omitted the risk of a collision. Fundamentally, ultimate control of the vehicle is still vested in the human driver, through either the low automation level of current ADAS or the ability to turn off ADAS. This limits the abilities of ADAS to prevent collisions. Furthermore, ADAS have limited ability to adapt to driver behavior, such as emotion-driven behavioral changes, which could help further reduce the risk of collision. Drivers experience various emotions due to the environment around them. These emotions influence the driving behavior of individuals which may lead to catastrophic consequences.

Emotions influence driving habits based on the *valence,* how pleasant or unpleasant an emotion is, they have for the individual. For example, a person experiencing anger – a negative valence emotion – may be more inclined to disobey speed limits or participate in reckless driving (Roidl, Frehse, and Höger 2014). Developing an *adaptive* driving assistance system, that could respond to changes in a driver's emotional state, could further reduce the probability of vehicle accidents.

BACKGROUND

Understanding and modeling of driver behavior started in 1938 with James Gibson and L.E. Crooks and the "Field of Safe Travel" theory. In their theory, drivers build a sense of comfort and safety in traffic by observing safety margins (e.g., minimum distances) between them and their surroundings (Gibson and Crooks, 1938). Since this first approach, the field has evolved to leverage the growing vehicle data ecosystem and advanced modeling approaches (AbuAli and Abou-zeid, 2016). While models of driver behavior have become more sophisticated, incorporating and improving ADAS and/or autonomous vehicle capabilities (Negash and Yang, 2023), relatively little attention has been devoted to integrating emotions in these models. The development of increasingly intelligent automotive systems, and the rise of more powerful data analytics techniques, has renewed interest in emotion recognition in the field of driver studies (Xiao et al., 2022). If emotions can be reliably detected, it may be possible to use that data to inform *adaptive* ADAS to further reduce vehicle risk. Although it is well understood that drivers experience emotions, with varying degrees of valence, the impact is different depending on the individual.

Emotions and Decision-Making

Emotions are a mental state of the human body that contribute to governing behaviors and stimulus reactions via immediate physiology and conscious cognition (Salzman and Fusi, 2010). There are involuntary changes due to emotions e.g. changes in facial expression, heart rate, and tension of muscles. Emotions produce immediate motivations to understand why the feeling is present and how behavior is changed to achieve or avoid these feelings in the future (Jang et al., 2019). Emotion classification and categorization has found eight primary emotions: joy, trust, fear, surprise, sadness, disgust, anger and anticipation (Dennison, 2024).

Emotions have an impact on overall judgement and decision making. Integral emotions, formed through experiences, "tag" objects and events with valence and intensity and enable us to discriminate good from bad options in a decision space (Västfjäll et al., 2016). Incidental emotions, including mood, represent the feelings at the time of a decision. While not normative, incidental emotions still have salience for the choice behavior (e.g., mood misattribution) (Lerner et al., 2015; Västfjäll et al., 2016). When driving, emotions can change based upon a variety of external factors which could change the course of action an individual takes behind the wheel. That is, driving behavior is influenced by both integral emotions formed from experience and incidental emotions that may be unrelated to driving.

Performance Influencing Factors (PIFs), also called performance shaping factors (PSFs), are characteristics that describe the context and situation in which human performance occurs (Paglioni and Groth, 2022). PIFs combine to create situations where errors are more or less likely than "nominal" (Mackieh and Çilingir, 1998). PIFs are affected by emotions indirectly through working memory use. Emotions can facilitate or hinder cognitive performance as they utilize valuable space in working memory which is utilized for decision making, problem solving and reasoning (Hou and Cai, 2022). With such effects, it can be deduced that emotions affect ones ability to make decisions, solve problems and perform adequate reasoning.

PIFs are used in human reliability analysis (HRA) methods to contextualize the scenario of interest. HRA methods incorporate various approaches to include PIFs, such as the multiplicative approach of Standardized Plan Analysis Risk Human Reliability Analysis (SPAR-H), where the product of all PIF multipliers adjusts a "nominal" or baseline human error probability to capture the impacts of context.

Advanced Driver Assistance Systems

ADAS have transformed driving by providing additional warnings and easing the collection of risk-relevant information for the driver (e.g., collision warnings) and transferring some driver-controlled behaviours to the vehicle (e.g., collision intervention). These are critical steps to reducing the risk to individuals from vehicle-related causes. In 2022 alone, the United States reported 5.93 million crashes and over 42,000 fatalities (NHTSA 2022; IIHS-HLDI 2024). ADAS is an umbrella term that includes multiple systems to assist the driver (Table 1). Broadly, ADAS can serve warning, intervention, control assistance, or non-control assistance functions. These functions can be linked to their respective automation levels ("Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles" 2021).

Table 1: Classification of ADAS and automation level. Adapted from (NHTSA, n.d.).

Classification	ADAS	Automation Level
Collision Warning	Forward Collision Warning	0
	Lane Departure Warning	0
	Rear Cross Traffic Warning	0
	Blind Spot Warning	0
Collision Intervention	Automatic Emergency Braking	0
	Pedestrian Emergency Braking	0
	Rear Automatic Braking	0
	Blind Spot Intervention	0
Driving Control Assistance	Adaptive Cruise Control	1
	Lane Centering	1
	Lane Keeping	1
	Piloting	2
Non-Control Assistance	Automatic High Beams	---
	Backup Camera	---
	Automatic Crash Notification	---

Clearly, the majority of available ADAS systems play either warning or brief interventional roles, and do not control the vehicle outside of specific parameters. This paradigm is changing as more vehicles are fitted with the more sophisticated driving *control* assistance technologies, including the advent of some “piloting” capabilities that can perform steering and pedal interfacing.

ANALYSIS

Emotions and Driving Behaviour

Changes in emotion state can lead to risk-relevant behavioural changes, such as changes in response time and altered risk perception. These in turn increase the likelihood of adverse consequences, e.g., a vehicle collision (M’bailra, 2018). Drivers indicating the feeling of stress prior to taking the wheel had elevated stress levels while performing the driving task, evidenced by increased braking frequency, intensity of braking and sudden acceleration. After completing the driving task, stressed drivers indicated they had high levels of fatigue. Other emotions also affect driving behaviours, as shown in Table 2.

Table 2: Selected effects of emotion states on driver behaviours.

Emotion	Effects	Significant	Source
Stress	Increased braking frequency Increased braking intensity Sudden acceleration	Yes	(Magaña et al., 2020)
Sadness	Increased acceleration rate Slowed reaction times	No	(Magaña et al., 2020)
Fatigue	Slowed reaction times Slowed acceleration and braking Continuous speed changes	Yes	(Magaña et al., 2020)
Happiness	Slowed reaction times	No	(Zimasa, Jamson, and Henson, 2017)
Anger	Higher error rate Riskier behaviour	Yes	(Jeon, Walker, and Yim, 2014; Pizzo, et al., 2024)

Drivers indicating the feeling of sadness performed differently than those indicating an initial stressed state. They accelerated faster and had been involved in more traffic accidents. Fatigued drivers had long reaction times to accelerate and brake while also consistently making changes of speed (Magaña et al., 2020). In general, negative emotions are more relevant for inducing risky driving behaviour, although there are some conflicting results for *sadness* and *happiness* and the significance of their impact (Zimasa, Jamson, and Henson, 2017; Jeon, Walker, and Yim, 2014; Pizzo et al., 2024; Magaña et al., 2020). Anger and sadness also reflected in slower reaction times than neutral emotions (Jeon, 2017).

Beyond the emotion itself, emotional valence (degree of positive or negative associated feeling) also contributes to determining driving differences. Valence can affect the reactivity, or strength of individual response (M’bailra, 2018). Drivers may experience a range from low reactivity (small changes in behaviour induced by emotional change) to hyper reactivity (immediate and strong change in behaviour). Hyperreactive individuals are 2.3 times more likely to be involved in a collision than those with basic emotional reactivity. Those with enhanced reactivity are 1.45 times more likely to be involved in a traffic collision against the same basic reactivity group. This displays that emotional effects relate directly to reactivity and the level of risk that drivers are willing to take (M'bailra, 2018).

Given the above, emotions are considered *internal* PIFs that can influence the human error probability (HEP) in multiple ways. Emotions can directly manipulate behaviors to influence the probability of error (e.g., by facilitating risky driving). Emotions can also indirectly influence behaviors by affecting other PSFs (e.g., time required to perform a task, perceived severity, communication, etc.). Intervening on emotional state, therefore, could be a way to reduce error-facilitating PIF states and reduce the "human error" (human-caused accident) probability in vehicles.

ADAS, Human Error, and Inconsistent Design

As shown in Table 1, several ADAS are now available that assume various functions from the human driver. These include warning (informational) systems like blind spot monitoring and lane monitoring, as well as control (actional) systems like adaptive cruise control (ACC), automatic emergency braking (AEB), and lane change assistance (LCA). Blind spot monitoring uses radar and computer vision to detect the presence of other vehicles in pre-determined blind spot zones defined by the original engine manufacturer (OEM). These sensors detect a vehicle in the blind spot and provide a warning indicator to the driver as a passive assistance system (Forkenbrock, et al., 2014). Lane monitoring is a passive system that locates the lines on the roadway and warns the driver with audio and/or haptic signals that they have crossed a lane line. The goal is to make drivers adjust their driving so they are not between different lanes of traffic. Neither of these systems, however, are capable of manipulating vehicle controls.

Adaptive cruise control (ACC) is able to manipulate powertrain and brake controls to maintain vehicle speed at a drivers desired speed depending on a user-selectable following distance to the next vehicle on the roadway. Some automakers have internal vehicle camera systems which identify driver eye position and will remind drivers to open their eyes and look at the road if necessary. ACC does require driver inputs through the steering wheel to ensure the driver still maintains control of the vehicle directional position when activated (Yu and Wang, 2022). Automated emergency braking (AEB) systems detect obstructions and apply the brakes to avoid a collision (Tan et al., 2020).

Lane change assist (LCA) is one of the most recent ADAS available in select vehicles. This system helps drivers make lane changes safely without driver input. Select automakers have started to utilize such features although they have been growing in popularity. This system is only available when the vehicle has blind spot monitoring and adaptive cruise control selected. Since this system is so new, very little information is available on its functionality and popularity amongst drivers (CARADAS, 2022).

The primary objective of ADAS is to mitigate the probability of human error resulting in injury, damage or death. PSFs are variable dependent upon the individual meaning each person would have a unique reaction in certain traffic situations (BasuMallik, 2022). Each individual approaches driving with their individualistic risk propensity as seen through the violation willingness scale and attitudes to driving violations scale (Rowe, Andrews, and Harris, 2013). In an effort to mitigate such concerns, ADAS provides a consistent driving technique determined as safe by each automaker. The number of available ADAS, the varying trade names and terminology, and the lack of training or educational information about *how* these systems work are particular problems for determining the safety impact of these systems (Pradhan, Hungund, and Sullivan, n.d.). ADAS has also been inconsistently designed, with the final design framework up to each automaker on how the system truly works. However, while data is still limited in some cases (Isaksson Hellman and Lindman, 2023), a growing corpus of crash data bears out the effectiveness of ADAS when equipped to vehicles (Spicer et al., 2018). It is reasonable to hypothesize that these systems would be more effective if capable of higher-order assistance, such as mitigating negative driving behaviors associated with adverse emotional states.

Emotion Detection Methodologies in Driving Contexts

Emotion detection and classification during the driving task is possible, but often requires invasive methods. In most approaches, the participant must be physically connected to various sensors and continuously monitored. The least invasive method of emotion detection is likely facial analysis using controller area networks (CAN) to store data, in parallel with heart rate monitoring which is minimally intrusive (Balali, Tavakoli, and Heydarian, 2020). Other studies have used visual cues such as head movement and facial expressions in parallel to the utilization of heart rate monitoring and steering wheel pressure (Nadai et al., 2016). Generally, parallelized approaches are fairly accurate (Zepf et al., 2021).

Electrocardiogram (ECG) measurements are a common and high-accuracy method for classifying driver emotions; in simulated environments ECG may achieve over 80% accuracy on discriminating anger and happiness (Minhad, Ali, and Reaz, 2017). Other methods, including electroencephalography (EEG), electrooculography (EOG), surface electromyogram (sEMG), galvanic skin response (GSR) and respiration rate, have been explored with varying success (Daza et al., 2013). Recently, studies have shown progress in using non-invasive methods, e.g., facial expression analysis, for emotion recognition without the need for invasive and/or distracting peripheral measurements (Xiao et al., 2022). As "big data" capabilities continue to improve, powered by advancing AI and ML methods, it is likely that fewer invasive measurements will be needed to accomplish in-situ emotion recognition for driver studies.

RESULTS

Emotions, whether formed while driving or prior to driving, significantly impact driving performance and safety. There are eight main emotions, of which anger, happiness, fear and anticipation are particularly salient for driving behaviors. Both the arousal (strength) and valence (positive or negative) of an emotion can adversely affect driver behavior. Happiness and anger were seen to take useful cognitive processing power away from drivers leading to less focus on the driving task which led to more dangerous driving behaviors and collisions amongst drivers.

Current ADAS provide powerful capabilities – both monitoring/warning and control that can improve driver safety. However, the effectiveness of ADAS appears limited by a lack of standard terminology in the automotive industry for the various capabilities, and a lack of driver familiarity with the technology, leading to mis- and/or dis-use. Finally, ADAS are not capable of adapting to driver behavior, and thus drivers experiencing emotional changes may deactivate or ignore ADAS.

Methodologies used to evaluate driver emotions are invasive including the need to wear various pieces of medical equipment and the utilization of expensive and large monitoring systems. These systems are currently unable to be incorporated into vehicles without significant space usage and inconvenience for drivers which do not want to make preparation for driving a longer process than it currently is. Of the methods used, the most common is heart rate measurements via ECG which is around 80 percent accurate at determining drivers emotion when paired with camera systems to evaluate facial expressions. More complex approaches included detection of electrical signals through the scalp, eyes, arm muscles and skin along with measurements of eye closure duration and frequency.

DISCUSSION AND CONCLUSION

This review has shown the importance of emotion in determining driver safety, as well as the benefits and limitations of ADAS in promoting safe driving behavior. However, one fundamental limitation of the effectiveness of ADAS is the "human component" – one piece of which is the tendency for humans to mis- or dis-use ADAS. As a result, the efficacy of ADAS on a vehicle may be dependent on the knowledge and emotional state of the driver. In response, some adaptable ADAS are available that will disengage if driver inattention is identified (e.g., through eye position and/or steering wheel touch tracking). If ADAS were similarly able to adapt to emotional state, for example applying tighter margins on lane centering, safely limiting the acceleration speed, or mitigating aggressive driving, the impact on road safety would be significant.

This review has further discussed that identifying emotion states is possible in the driving context. Although currently limited by relatively invasive, intrusive, or distracting methods, advancing "big data" analytic capabilities through, e.g., artificial intelligence (AI), point to the future feasibility of using low-intrusion facial recognition or even driving behavior characteristics to identify emotional states. It is already possible to discriminate between drivers with vehicle data (Ezzini, Berrada, and Ghogho, 2018; Biggs et al., 2024); A similar process could be leveraged to discriminate between emotional states of the same driver.

More adaptive ADAS could leverage existing driver input checks to ensure that the driver is maintaining control over the vehicle, and incorporate additional measurements like eye position and in-cabin audio to judge driver emotional state. These can be further augmented by evaluating trends in driving behaviors; the control module can record, e.g., pedal positions and steering wheel angle. With these capabilities, it is possible to identify different emotion states and adverse behaviors a driver commonly displays, as well as the driver's preferred driving style. Not only would ADAS then be able to mitigate adverse behaviors but it could mimic the driver's preferred style, making it more likely the driver keeps ADAS activated. With ADAS activated more frequently, further accidents may be reduced while driver satisfaction is maintained.

Evaluation of emotions allows automakers and lawmakers to understand what causes accidents so frequently so that more systems can be incorporated to help reduce the number of accidents for the future. An understanding of current ADAS capabilities provides an understanding of what technology is available in today's vehicles and how that may change in the future. Understanding emotion measurement techniques is also helpful to see what methods work well to evaluate driver emotions accurately and which methods to stay away from. Next steps for this evaluation are to understand how accurate emotion identification techniques can be obtained quickly and how the use of systems such as automated intelligence (AI) could be used to assist with emotion identification as every individual is different. This would then lead into what systems would need to be added into automobiles to ensure that ADAS can adapt to driver emotions and provide preferred driving styles for each individual while keeping safe driving behaviors with other vehicles on the road.

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