Physiological Measurements in Automated Vehicle-Pedestrian Research: Review and Future Opportunities

YIYUAN WANG, Design Lab, Sydney School of Architecture, Design and Planning, The University of Sydney, Australia

TRAM THI MINH TRAN, Design Lab, Sydney School of Architecture, Design and Planning, The University of Sydney, Australia

MARTIN TOMITSCH, Transdisciplinary School, The University of Technology Sydney, Australia

Physiological measurements have been widely used to study interactions between automated vehicles (AVs) and drivers, yet they have received little attention in AV-pedestrian interaction research. This paper reviews nine articles from a systematic query, outlining the current state and proposing future opportunities for using physiological measurements in this area. Our findings reveal a targeted application of these measures, with gaze fixation predominantly used to assess visual attention and electroencephalogram employed to evaluate emotional valence and cognitive workload. The review highlights the motivation (e.g., supporting the comparison of multiple experimental conditions), implementation (e.g., equipment, physiological indicators, and their inferred states), and impact (e.g., facilitating exchanges with self-reported measures) of using these measurements. Moreover, we offer promising directions for future research, laying a foundation for further incorporating physiological measurements in AV-pedestrian studies and advancing objective and quantitative methods in this field.

1 INTRODUCTION

How humans interact with automated vehicles (AVs) has garnered significant research attention within the automotive user interface (AutoUI) community since the advent of advanced driver assistance systems [37]. In evaluating interaction performance, e.g., for the purpose of designing better user experiences or ensuring safety through AV feedback mechanisms [29], both subjective reports and objective measurements have been widely adopted to understand drivers' mental states and behaviours [10, 23, 33].

Physiological measurement serves as an objective method to obtain quantitative data about drivers' mental states by collecting physical or biological parameters of the human body, typically through specialised medical devices and sensors [1, 39], such as electrodermal activity (EDA) and heart rate variability (HRV). These measurements have shown importance in studying the affective and cognitive responses of drivers [31, 32, 34], which in turn informs the design of in-vehicle features, such as regulating negative emotions [5] and early intervention for fatigue [35, 49].

With the rise of the self-driving era, more AutoUI research has studied how pedestrians interact with AVs [4, 18, 42], as future AVs are expected to be equipped with external Human-Machine Interfaces (eHMIs) for communication with pedestrians in the absence or inattention of drivers [8, 25]. However, eHMI studies to date have mostly employed self-reported measures [14], including questionnaires and interviews, or behavioural metrics, such as crossing onset time [12]. Physiological measurement presents a nascent opportunity for gathering objective, quantitative data about pedestrians' bodily and mental responses to AVs' external interactions. It is worth investigating how physiological measurements have been utilised in eHMI research and what future opportunities exist.

In this paper, we present a review of physiological measurements in current AV-pedestrian studies concerning the external interaction of AVs. We centre the review around the following research questions (RQ):

- (RQ1) Why are physiological measurements employed in the reviewed studies?
- (RQ2) How are the physiological measurements implemented in the studies?
- (RQ3) What is the impact of using physiological measurements in the studies?

Section 2 presents related work in AV domains. Section 3 describes the review method. Section 4 reports on findings from the review. Section 5.1 highlights recommendations for future avenues.

2 RELATED WORK

2.1 Evaluation Methods in AV Research

Evaluation methods in human-machine interface (HMI) research can be categorised into subjective evaluation, behaviour evaluation, and physiological measurement [39]. In AV research, subjective evaluations often involve self-reported data, such as questionnaires and interviews, where participants provide feedback on their experiences and perceptions [14]. Behaviour evaluations involve observable actions and reactions, such as driving performance metrics (e.g., reaction time, braking distance) and task performance (e.g., error/accuracy in completing a task) [12, 36]. Facial expressions and eye gaze are also considered behavioural responses in some studies [3, 33, 36, 47]. Physiological measurements, on the other hand, refer to involuntary responses related to living organisms' bodily reactions [1]. Under this definition, behavioural responses differ from physiological responses in that they can be controlled voluntarily [3]. However, certain measures, such as eye tracking, are not clearly categorised as either behavioural or physiological. This ambiguity arises when metrics like pupil diameters are included [28, 32], as they encompass both voluntary and involuntary aspects.

2.2 Physiological Measurements in In-Vehicle Studies

Physiological measurements are widely used in driver and passenger simulators to obtain quantitative data about physiological states, such as through electrocardiogram (ECG) [28, 46] and electroencephalogram (EEG) signals [40, 45]. These measures are important to gauge metrics pertinent to safe driving behaviours, including stress level [16, 46] and cognitive distraction [28, 35]. Measurements like EDA, HRV, and facial temperature are also important for studying the emotions or affective states of drivers [23, 31, 32, 34] as well as passenger comfort and anxiety levels [10, 29]. Applications benefited from physiological measurements range from the design of comfortable driving styles [10], to the prediction of driving risks [49], to mood induction or regulation [13].

2.3 Advantages of Physiological Measurements

Physiological measurements enable direct acquisition of user data, offering a "hands-off" evaluation approach and a reduced intrusion to user tasks [17, 45]. These features can be crucial for adaptive automation systems that adjust their feedback or information display in real-time to human states [36, 38, 45]. Physiological data has the potential to accurately estimate perceptual attributes. For example, a study found that physiological signals could better predict perceived safety compared to facial features extracted from videos when using subjective perceived safety as labels [1]. Moreover, simulation-based settings, such as virtual reality (VR) and driving simulators, can easily integrate physiological sensors [22, 39], optimising the understanding of user performance during the rapid prototyping of different interfaces and requirements [22, 39].

In summary, physiological measurements have been employed in many applications for automated driving [36], while AV-pedestrian studies mainly use self-reported questionnaires or behavioural measurements as quantitative methods [36]. Some eHMI studies have advocated for considering physiological factors [17, 43]; for example, theories of human colour receptivity (e.g., chromatic sensitivity, colour vision deficiencies) have been used to inform appropriate eHMI colours [43]. Therefore, this paper further contributes to the understanding of current empirical utilisations of physiological measurements in eHMI studies and highlights future research opportunities.

3 METHODOLOGY

Figure 1 summarises the article selection process for the scoping review. We queried Google Scholar as it covers a broad search across various sources of publications. We searched for all dates for "automated vehicles", "physiological", "external interactions", "pedestrians" as well as their synonyms: "automated cars", "autonomous vehicles", "autonomous cars", "self-driving vehicles", "self-driving cars", "driverless vehicles", "driverless cars"; "physiology"; "external communications", "external interfaces", "external human-machine interfaces", "eHMIs". The last search on 31 May 2024 yielded a total of 166 results, including top publishers in automotive research fields such as ACM (16), IEEE (14), MDPI (14), Elsevier (11), Springer (8), Sage (6), Taylor & Francis (4), and Frontiers (4).

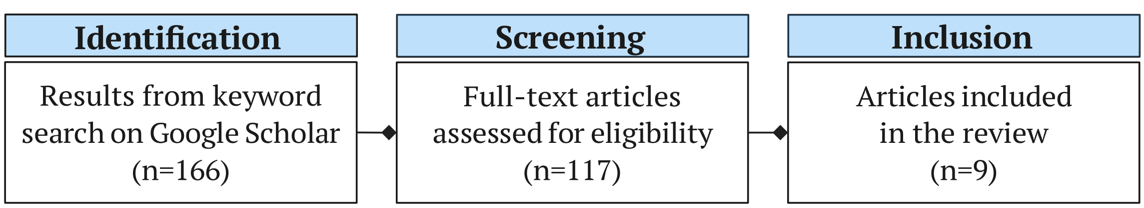

Fig. 1. Flow diagram depicting the article selection process.

Among the 166 search results, 117 of them were full-text articles. Subsequently, we conducted a screening on the 117 articles and selected articles if they (1) were published in peer-reviewed conferences/journals or book chapters; (2) involved physiological measurements in empirical user studies; (3) investigated interactions between AVs and pedestrians. Finally, 9 articles (9 studies) were included in the review. Eye tracking can be considered either a behavioural or physiological measure (see Section 2.1). In our screening process, we included eye-tracking articles because some measured pupil diameters [11, 27], or considered eye-tracking variables as physiological [20]. To ensure unbiased screening, we included all articles using eye tracking that appeared in the keyword search results. The first and second authors independently reviewed the nine articles based on the three research questions, followed by discussing and merging their findings in meetings.

Table 1. Implementation of physiological measurements in the reviewed studies.

Article	Equipment	Indicators	Inferred States	Study Setting	Other Data
Chang et al. [6]	Empatica E4 wristband	Electrodermal activity (EDA) / skin conductance response (SCR), heart rate (HR), heart rate variability (HRV)	Frequency of being stimulated	VR lab study, participants sitting	Questionnaires, interviews, crossing decisions by button-pressing and head rotations
Eisma et al. [11]	Eyelink 1000 Plus eye-tracker	Gaze movement dispersion, number of saccades, pupil diameter (gaze-contingent approach)	Visual attention on eHMIs, mental workload	Monitor-based lab study, sitting	Questionnaires, response time by keyboard-pressing
Gruden et al. [15]	Tobii Pro 2 eye-tracker	Number and duration of gaze fixations	Visual attention on traffic elements and on phone	Field study, standing, walking	Crossing behaviours by video footage analysis
Jayaraman et al. [20]	Pupil Labs eye-tracker	Duration of gaze fixations	Observable trusting behaviours indicated by pedestrians' time spent looking at approaching AVs	VR lab study, standing, walking	Questionnaires, crossing behaviours
Luque et al. [26]	Brain Products GmbH	Electroencephalogram (EEG)	Event-related potentials (ERP): Electrophysiological response of the brain to an (internal or environmental) event, cognitive workload	VR lab study, standing, walking	Questionnaires, estimation of vehicle arrival by controller-pressing, movement recordings
Lyu et al. [27]	Tobii Pro Spectrum eye-tracker	Number and duration of gaze fixations, pupil diameter	Visual attention on eHMIs and AV components	Monitor-based lab study, sitting	Questionnaires, crossing decisions by keyboard-pressing
Lanzer et al. [24]	Vive Pro Eye VR headset	Number and duration of gaze fixations	Visual attention on traffic elements, phone, and other pedestrians	VR lab study, standing	Questionnaires, interviews, movement recordings, task error rate on virtual phone
Park and Kim [30]	Emotiv Epoc X	Electroencephalogram (EEG)	Valence (positive or negative) of emotions	VR lab study, unspecified participant movement	Questionnaires, head tracking
Zhao et al. [48]	Tobii Pro 2 eye-tracker	Number and duration of gaze fixations	Gaze patterns towards overall scenes, vehicles, and vehicle components	Field study, standing, walking	Not specified

4 RESULTS

4.1 Motivation (RQ1)

4.1.1 Supporting the comparison of multiple experimental conditions. One common motivation for using physiological measurements is to provide a quantitative method to support the comparison among experimental conditions (N=3). This includes comparing the frequency of stimulation by different gesture-based eHMIs via SCR, HR, and HRV [6], the valence of pedestrians' emotions towards varying automation levels of urban street configuration indicated by EEG [30], and pedestrians’ attention allocation and response time towards text- or light-based eHMIs using a gaze-contingent approach [11].

4.1.2 Informing attention distribution in complex traffic scenarios. In our review of eye-tracking articles, most studies use eye-tracking to understand how pedestrians distribute their attention in various traffic situations beyond the typical one AV-one pedestrian crossing (N=4). This includes examining pedestrians' visual attention to two AVs and different eHMI designs [27], the distraction of smartphone use or the presence of other pedestrians in addition to eHMIs [24], the distraction of phone use while crossing different types of signalised crossings [15], and systematically measuring pedestrian gaze patterns towards the overall scene, vehicles, and vehicle components before crossing [48].

4.1.3 Enhancing methodological setup of user evaluation. Physiological measurements can be integrated into user evaluations to enhance typical HCI evaluation methods used for AV-pedestrian studies (N=2). One study established the relationship between self-reported trust and observable trusting behaviours in pedestrian-AV crossing interactions, using gaze fixations as indicators of trusting behaviours [20]. Another study examined the effectiveness of integrating EEG with VR, accurately assessing cognitive workload during pedestrian road-crossing scenarios [26].

4.2 Implementation (RQ2)

Table 1 presents the implementation of physiological measurements in the reviewed studies concerning equipment (devices or sensors), indicators (physiological responses measured), inferred states (interpretation of pedestrian mental states), study setting (study type, pedestrian position when wearing the equipment), and other data collection methods.

4.3 Impact (RQ3)

4.3.1 Enhanced insight from objective measurement of perception. The EEG measure demonstrated the potential for accurately studying pedestrian perceptions, including cognitive workload [26] and emotions [30], supporting the digital twin environment for AV-pedestrian interactions [26, 30]. Additionally, the SCR measure offered quantitative data to better understand the visual stimulation of gesture-based eHMIs [6].

4.3.2 Facilitated exchanges with self-reported measures. Common self-reported measures in AV-pedestrian studies, such as trust and cognitive workload, were found to be modelled by physiological measurements. Observable trusting behaviours inferred by gaze duration showed a strong correlation with self-reported trust [20], and cognitive processing signals could be precisely assessed via EEG [26]. These physiological measurements showed the potential to serve as a proxy for measuring self-reported variables and enabling real-time assessment as participants performed tasks [15, 20].

4.3.3 Practical applications for design and behaviour modelling. Gaze indicators revealed how pedestrians allocated their attention to different street design typologies [15] and to different eHMI designs [11, 27], informing design implications such as the importance of considering peripheral vision when designing eHMIs [11]. Additionally, understanding the distribution of gaze in space and across different traffic elements is fundamental to modelling pedestrian road-crossing behaviours [48].

5 DISCUSSION

5.1 Research Opportunities

5.1.1 Support evaluating multimodal eHMIs. The effectiveness of communication between eHMIs and pedestrians can depend on the information receiver's current physiological state, such as distraction or fatigue [44]. Insights from cognitive psychology indicate that tasks using the same cognitive resources can interfere with each other more than those using different resources (e.g., linguistic vs. pictorial information) [44]. As identified in our review, physiological measurements such as EEG can precisely gauge cognitive workload [26]. This demonstrates their potential for assessing cognitive processing across different modality combinations to determine which combination is most effective and least mentally demanding for pedestrians.

5.1.2 Support developing real-time adaptation to pedestrians. Physiological measurements enable the retrieval of data about pedestrians' mental states without intruding on their tasks or waiting until the task session ends [15, 45]. This allows eHMIs to adapt to user profiles in real-time or predict users' behaviours and mental states shortly into the future, increasing the personalisation of interfaces and potentially improving safety and efficiency in traffic [5, 35, 49].

5.1.3 Support measuring unconscious errors. The objectivity of physiological measurements and their ability to assess human states in real time can be utilised to detect pedestrians' unconscious errors during task performance. A study found that humans' ability to detect alarms unconsciously decreases when events occur in synchronisation with heartbeats, suggesting the value of developing human reliability assessments during events [41]. Applications include calibrating pedestrians' trust (or overtrust) towards eHMIs [18] and their perceived safety towards AVs [1] in addition to self-reports and behavioural measurements.

5.1.4 Integrate with virtual reality simulations. Physiological equipment has shown promise for integration with VR simulations [19, 26]. In our review, 78% of the studies used physiological equipment in lab settings, with 71% of these involving VR simulations and the rest using monitor-based videos. The two field studies used mobile eye trackers. Controlled lab environments are beneficial for setting up sophisticated physiological devices, as participants have limited movements and follow predefined procedures. Additionally, our review found that physiological measurements can effectively capture human perceptions and mental states, comparable to real-world settings, showing promise for supporting the development of digital twins for transportation research [26, 30].

5.1.5 Explore intrusiveness of equipment on participants. Literature on affect detection methods has documented varying levels of intrusiveness of physiological measurements when measuring the affective states or emotions of users [21, p.19]. Systematically understanding the intrusiveness of equipment on natural behaviours, comfort, and the feasibility of wearing them simultaneously with other devices (e.g., VR headsets) will be crucial for supporting the adoption of physiological measurements.

5.1.6 Augment behaviours of road users. There is increasing popularity and availability of commercial-grade physiological sensors, such as smartwatches and bike monitors [2]. These sensors provide a way to continuously record physiological states from road users over time, resulting in detailed datasets that can reveal habitual behaviours. Future research can distribute commercial-grade sensors to understand pedestrian behaviours in naturalistic environments.

5.2 Limitations and Future Work

As an exploratory work, this review did not encompass all articles relevant to AV-pedestrian research. Employing a snowballing query method (i.e., examining references within the reviewed articles) could have increased the number of eligible articles. Additionally, the search results did not include some eye-tracking studies on traditional vehicle-pedestrian interactions that provide implications for AV-pedestrian interactions [7, 9]. Future work may consider expanding the scope of this review or connecting it with current research on in-vehicle physiological measurements.

6 CONCLUSION

We reviewed nine articles on the use of physiological measurements in empirical AV-pedestrian interaction studies. Our findings showed a targeted application of these measures, with gaze fixation primarily assessing visual attention and EEG evaluating emotional valence and cognitive workload. We reported on the motivation, implementation, and impact of using physiological measurements. Additionally, we identified six research opportunities for future studies. This work lays a foundation for incorporating physiological measurements in AV-pedestrian research and advances the dialogue on objective and quantitative methods in this field.

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