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ORIGINAL RESEARCH

On validating a generic camera-based blink detection system for cognitive load assessment

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Abstract

Detecting the human operator's cognitive state is paramount in settings wherein maintaining optimal workload is necessary for task performance. Blink rate is an established metric of cognitive load, with a higher blink frequency being observed under conditions of greater workload. Measuring blink rate requires the use of eye-trackers which limits the adoption of this metric in the real-world. The authors aim to investigate the effectiveness of using a generic camera-based system as a way to assess the user's cognitive load during a computer task. Participants completed a mental task while sitting in front of a computer. Blink rate was recorded via both the generic camera-based system and a scientific-grade eye-tracker for validation purposes. Cognitive load was also assessed through the performance in a single stimulus detection task. The blink rate recorded via the generic camera-based approach did not differ from the one obtained through the eye-tracker. No meaningful changes in blink rate were however observed with increasing cognitive load. Results show the generic-camera based system may represent a more affordable, ubiquitous means for assessing cognitive workload during computer task. Future work should further investigate ways to increase its accuracy during the completion of more realistic tasks.

KEYWORDS
active vision, cognition, human-robot interaction

1 | INTRODUCTION

Cognitive load is the demand for cognitive control imposed by a task [1]. Maintaining optimal cognitive load is necessary for effective task performance. Conditions of non-optimal load wherein the combined cognitive task demand is either too low (underload) or too high (overload) for the user are associated with performance declines and increased safety risks in safety-critical tasks. For example, completing activities like driving or product assembly under high cognitive load often leads to poorer task performance and a greater risk of collisions or work injuries [2–5]. Likewise, cognitive underload resulting from, for example, boredom, are associated with performance declines in tasks requiring prolonged attentive engagement [6, 7].

Detecting the human operator's cognitive state is paramount in settings wherein maintaining optimal workload is necessary for task performance and safety. In human–machine interaction, prior research has used neurophysiological metrics for the robotic agent to detect the user's state. For example, Bird et al. [8] and Aldini et al. [9] used electroencephalography as a way for the intelligent agent to detect the user's state and adapt its behaviour to the characteristics of the human operator. In clinical settings, state detection systems have been proposed for the development of computer aids that, through adapting their interface based on the user's cognitive and emotional state, can help with the treatment and enhancement of conditions like anxiety and autism [10, 11].

Cognitive load is often assessed through measuring the human operator's performance in secondary tasks. Simple stimulus detection tasks wherein the user is instructed to press a button in response to the presentation of an intermittent stimulus are common for assessing the load of the primary task at hand (e.g. [12]). Changes in cognitive load manifest through changes in detection performance, with greater load resulting

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in longer response times [13, 14]. Given their simplicity, researchers have adopted these assessment tasks in a variety of applied settings, including driving, human-computer interaction, and lie detection [15–17]. However, because they require the completion of a behavioural task demanding consistent attentional engagement, it is argued that they incur in an added cognitive cost [18, 19].

Eye metrics are commonly used for cognitive load assessment. For example, blink rate which is the frequency of eye blinking is found to track fluctuations in cognitive load. Magliacano et al. [20] had participants complete an oddball auditory task wherein they were instructed to actively count the number of auditory tones. With the task becoming more taxing, a spike in blink frequency was observed. Consistent patterns are also found outside laboratory settings. For example, in a recent study participants completed manufacturing tasks requiring repeated full-body motions in two conditions of low and high cognitive demand [2]. As the cognitive demand of the task increased, this resulted in a higher blink rate. Faure et al. [21] found consistent patterns during simulated driving wherein, as the difficulty of the secondary cognitive task increased, this led to more frequent blinking (also, see ref. [22]). Blink rate can be measured via either electrooculography (EOG) or optical eye-trackers. The former requires the use of contact sensors placed on the user's eye muscles to record changes in voltage. The latter record the amount of infrared light emitted by infrared beams and reflected off of the pupil to estimate eye closure, and require the use of either head-mounted of remote equipment (see Table 1). Because both approaches require the use of contact equipment and laborious data processing, these pose a limitation to the ability to record blink rate in everyday settings.

To tackle this issue, recent work has tested alternative, non-invasive ways for recording eye blinks that use ubiquitous, widely available camera technology. For example, Al-Gawwam and Benaissa [23] estimated the aperture of the eyes via extracting users' facial landmarks from a generic video. This information was then compared against a set threshold to determine the occurrence of eye blinks. Dewi et al. [24] adopted a similar approach. In their work, they applied the dlib algorithm [25] to generic video footage to estimate the aperture of each eye based on six facial landmarks: two for the upper eyelid, two for the lower eyelid, one for the medial canthus, and one for the lateral canthus. A threshold known as eye-aspect ratio was calculated so that a blink was detected every time the aperture of the eyes fell below the set threshold ([26, 27], used similar methodologies for eye blink detection). In their follow-up work, Dewi et al. [24] used a similar camera-based approach for driver state detection. Facial landmarks were first extracted from a generic camera video and compared against the set threshold to determine eye blinks. Changes in blink rate were observed in conditions of underload (consistent patterns are observed in refs. [28, 29]).

Although promising, the above work failed to validate the proposed approach using more established means for measuring eye blink. In particular, whereas blink rate was recorded using generic camera-based systems, these studies lacked the use of reliable metrics to help estimate these systems' accuracy. In addition, what is also missing is information on how accurate these systems are in tracking dynamic changes in cognitive load during continuous tasks. To tackle this issue, the current study aims to:

1. Adopt a scientific-grade eye-tracker to test the accuracy of a generic camera-based approach for eye blink detection. If the camera-based approach is accurate, we expect the resulting blink rate not to be different from the one obtained using the scientific-grade eye-tracker.
2. Investigate the accuracy of the generic camera-based approach in tracking changes in cognitive load. A higher blink rate is expected with greater cognitive task demand.

To achieve this, we have participants complete a cognitive task with increasing levels of difficulty. The generic video feed from a ubiquitous camera is processed using a threshold-based approach similar to that used in Dewi et al.'s [24] to estimate eye blinks. Its output is validated using the blink rate from a scientific-grade eye-tracker. Cognitive load is measured through tracking participants' performance in a single stimulus detection task.

TABLE 1 Examples of approaches for measuring eye blink.

Method for detecting eye blinks	Example
Optical eye trackers measure the amount of infrared light reflected off of the pupil to estimate eye closure.	 Courtesy of Pupil Labs.
Electrooculography (EOG) measures the electrical potential between electrodes placed at points close the eye to estimate eye blink.	 Courtesy of Mind Media.

2 | METHOD

2.1 | Participants

Twenty-five volunteers (18 men, 7 women) were recruited from the University of Windsor student population and received a

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$10 Amazon gift card in exchange for their participation. Their age ranged between 18 and 32 years old ($M = 23$, SD = 5.3). A sample of younger participants was selected to limit possible confounding effects of age on cognitive processing. Participants had no prior experience completing the stimulus detection task. They all had normal or corrected-to-normal hearing and sight. The research complied with American Psychological Association Code of Ethics and was approved by the University of Windsor Research Ethics Board (#19–045).

2.2 | Design

A design with two within-subject factors was considered. The first factor, blink detector, had two levels: generic camera-based and eye-tracker. Eye blinks were computed using both a generic camera-based system and a scientific-grade eye-tracker that were both operational throughout the study (more information in the procedure and equipment section). The second factor, cognitive task difficulty, was manipulated by having participants complete one of three versions of a cognitive task: easy, medium, hard, each producing increasing levels of cognitive task demand (more information in the procedure and equipment section). Dependent variables were: blink rate (in blinks per minute) produced by the generic camera-based system; blink rate (in blinks per minute) produced by the eye-tracker; response times in the single stimulus detection task (in seconds); self-reported cognitive load ratings.

2.3 | Procedure and equipment

Upon entering the laboratory environment, participants were instructed to complete the consent form and share their demographics information. After being provided with an overview of the study, the familiarisation phase begun, which consisted in participants becoming acquainted with the experimental setup including the webcam, eye-tracker, the cognitive task, and the single stimulus detection task.

2.3.1 | Generic camera

A generic webcam that is widely available at office supply stores and online retailers was used for this study. The NexiGo N660P (NexiGo Inc., USA) has a resolution of 1080 pixels and a sampling rate of 60 frames per second. During the familiarisation and experimental phases, the webcam was placed on top of an AOC 27-inch screen with a resolution of 1920 × 1080 connected to a PC running Windows 10. Participants sat on an office chair at a distance of approximately 50 cm from the screen with the webcam directly pointed at their face. The video footage from the experimental phase was recorded and processed for eye blink detection after the study (see data processing and analysis). A schematic of the experimental setup is presented in Figure 1. After having been seated, participants received instructions on the eye-tracker and calibration process.

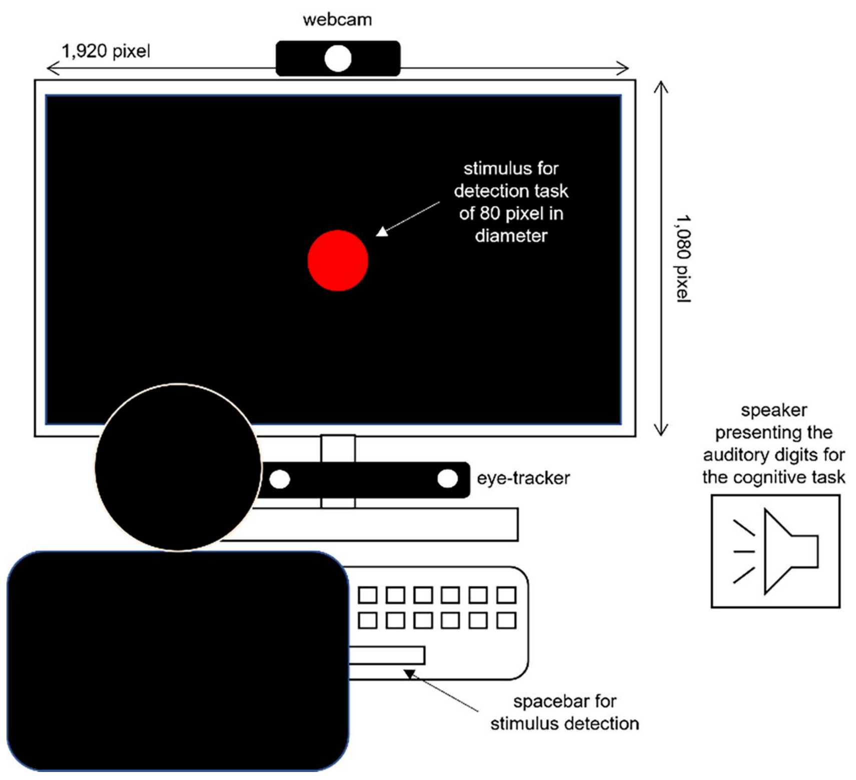

FIGURE 1 Schematic of the experimental setup.

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2.3.2 | Eye-tracker

A remote Gazepoint GP3 eye-tracker (Gazepoint Inc., Vancouver, BC, Canada) with data collection frequency of 60 Hz was used. Previous research shows this as a reliable tool for desktop-based eye-tracking [30–32]. The eye-tracker has a graphical user interface which was used for the calibration process. During the calibration process, participants were instructed to fixate on a red circle which moved to occupy nine distinct positions on the screen. At the end of the calibration, participants were instructed on how to complete the cognitive task.

2.3.3 | Cognitive task

The auditory version of the n-back task [33] was used as the cognitive task as it allows to easily manipulate levels of cognitive task demand, and it produces levels of cognitive load comparable to those experienced when performing everyday activities [14, 34, 35]. For this task, participants listen to a series of digits randomised between zero and nine and presented at intervals of 3 s. Their task is to repeat aloud one of the previously presented digit. In our study, we considered three levels of cognitive task difficulty: easy, medium, hard. In the easy condition, participants did not complete the task (control). In the medium condition, participants were instructed to repeat aloud the last digit that was presented to them. In the hard condition, participants were instructed to repeat aloud the third-to-last digit in the series. During the familiarisation phase, participants received instructions on how to complete this task and were given all the time they required to practice it. After practicing this task, participants were instructed on how to complete the single stimulus detection task.

2.3.4 | Single stimulus detection task

For this task, participants were presented with a red circle with a radius of 80 pixels that was located at the centre of a black background of the same size of the screen. The stimulus was presented randomly every 3–5 s and required participants to detect it by pressing the spacebar on the keyboard as quickly as possible. This task was created using the Python's Pygame library. Response times (in seconds) were recorded. Note that this task was modelled after the visual version of the ISO Detection Response Task [1], which is a standard protocol for measuring cognitive load. This was done to ensure the validity and accuracy of our methodology in assessing levels of participants' cognitive load. During the familiarisation phase, participants received instructions on how to complete this task and were given all the time they required to practice it. After the practice was over, the experimental phase begun.

2.3.5 | Self-reported load

Participants were also familiarised with the scale for assessing the cognitive load of the task at hand. They were asked to rate on a scale from 0 (very low) to 100 (very high) the level of cognitive load experience during the experimental condition. This scale was modelled after mental demand scale of the NASA-TLX questionnaire [36].

2.3.6 | Experimental phase

During the experimental phase, participants completed three experimental conditions wherein the difficulty of the cognitive task was manipulated: easy, medium, hard. Each condition lasted 4 min. Participants completed the single stimulus detection task concurrently with the cognitive task. A video footage of the participant's face was recorded throughout the experimental phase, and later processed for eye blink detection (see data processing and analysis section). Blink rate was also measured using the Gazepoint eye-tracker. The presentation of the three conditions was counterbalanced using a Latin square design [37]. At the end of each condition, participants reported their subjective cognitive load ratings. The next condition commenced when participants felt ready to do so. When all three conditions were completed, participants were dismissed.

2.4 | Data processing and analysis

2.4.1 | Generic camera-based eye blink calculation

The generic camera-based eye blink calculation was conducted as follows (for similar approaches, see refs. [24, 27, 29]). First, a Histogram of Oriented Gradients (HOG) based face detection algorithm [38] was applied to a particular frame. The result of this algorithm is the coordinates of a rectangle encapsulating the human face in the frame. From this region of interest covering the human face, shape prediction algorithms that are capable of localising key points were applied. After the coordinates of the rectangle were localised, the dlib-facial landmark detector based on Rosebrock [39] was applied. This detector algorithm provides 68 landmarks (X and Y coordinates) distinguishing different features of the participants' faces (Figure 2). Of these landmarks, the ones of interest are coordinates 37–41 corresponding to the right eye and coordinates 43–47 corresponding to the left eye. These eye landmark positions on the frame are used to calculate the scalar value called Eye-Aspect Ratio (EAR). The formula below shows how EAR was calculated for the left eye; a similar formula was used for the right eye.

$$\mathrm{EAR}_{left\ eye} = \frac{\|p_{38} - p_{42}\| + \|p_{39} - p_{41}\|}{2\|p_{37} - p_{40}\|}$$

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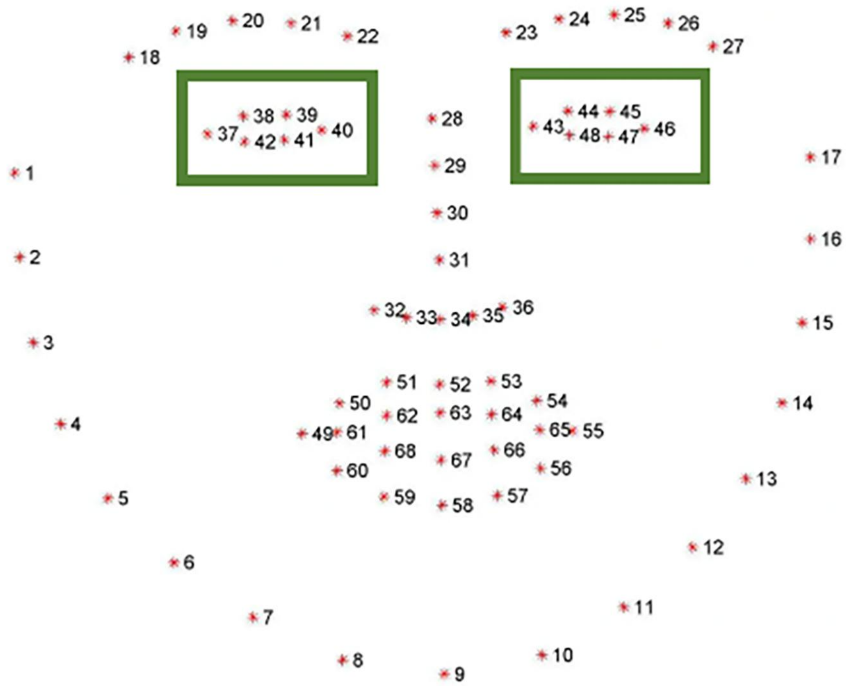

FIGURE 2 Sixty-eight facial landmarks detected through the dlib library. Landmarks of interest for the right and left eye are surrounded by green rectangles.

where

p_{38}, p_{39} are the landmarks corresponding to the left eye's top eyelid,

p_{42}, p_{41} are the landmarks corresponding to the left eye's bottom eyelid,

p_{37} is the landmark corresponding to the left eye's medial canthus, and

p_{40} is the landmark corresponding to the left eye's lateral cantus.

EAR was calculated individually for each eye, and then averaged across the two eyes. Recorded EAR values were then compared against a threshold to determine the occurrence of eye blinks. In the studies by Dewi et al. [24] and Pandey and Muppalaneni [27], fixed thresholds were selected. This proved effective considering that it was applied to relatively short videos recorded from one individual participant. Given our distinct experimental design wherein the recorded videos had longer durations and participants' oculomotor behaviour was expected to change under diverse levels of cognitive task demand, we decided to adopt an adaptive threshold. The average EAR was calcualted for a video that was recorded at 60 Hz. Due to this high sampling, the resulting EAR was very noisy. For this research, a moving average filter was employed to remove noise. This process is represented in Figure 3 wherein the blue line represent the average EAR (of the left and right eye combined) and the red line represent the smoothed data.

Each 4-min video was then split into forty-eight 5-s time windows. Considering that a normal blink rate is approximately 12 blinks per minute [40, 41], the duration of each 5-s window was determined so at least one blink would fall within each window. Mean and standard deviation (SD) of EAR were calculated for each window. Within each window, a threshold of 2-SD below the mean was set. This was empirically determined as being the most accurate among alternative approaches (e.g. 1-SD, 1.5-SD, 2.5-SD, and 3-SD below the mean). The duration of individual eye blinks approximates 250 milliseconds [42–44]. With this in mind, considering that webcam's sampling rate of 60 Hz, a threshold of 15 consecutive frames was set for blink detection. This means that, to be classified as a blink, the recorded EAR must fall below the adaptive threshold (means -2-SD) for at least 15 consecutive frames, else it would be classified as a non-blink. This procedure was applied to all three experimental conditions so that blink rate (in number of blinks per minute) was computed for the easy, medium, and hard cognitive task conditions.

2.4.2 | Eye-tracker eye-blink calculation

The Gazepoint eye-tracker output the number of eye blinks recorded in each condition for each participant. A research assistant visually inspected the output to ensure no artefacts were present. The output from the Gazepoint eye-tracker was used to compare the output of the generic camera-based eye blink calculation.

2.4.3 | Single stimulus detection task

Following the ISO DRT protocol (2016), response times shorter than 100 ms and longer than 2500 ms were removed and no longer analysed. Average response times (in milliseconds) were calculated in each of the three experimental conditions for each participant.

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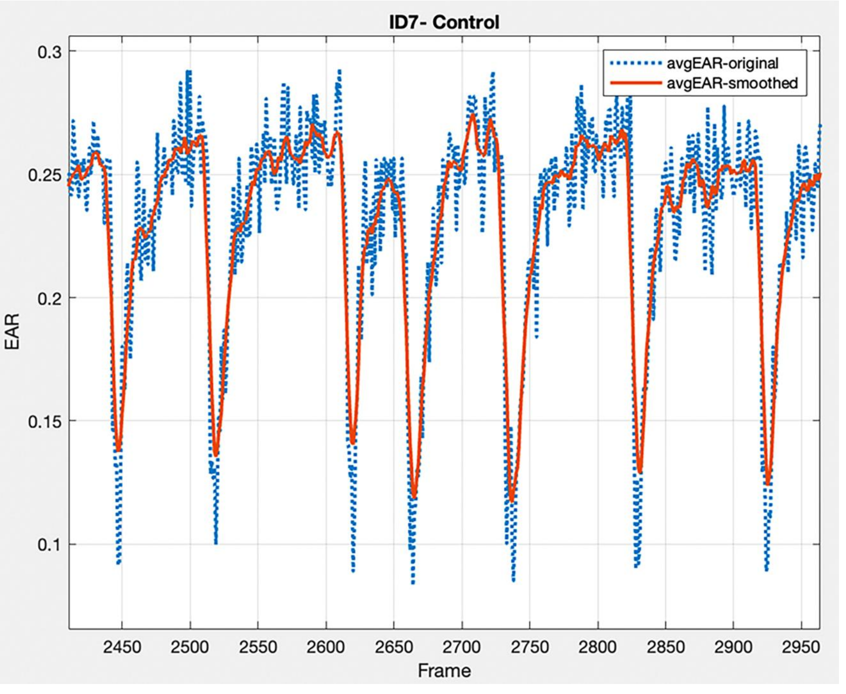

FIGURE 3 Raw and smoothed EAR.

2.4.4 | Self-reported load

Mental load self-reported ratings were processed for each participant and condition.

2.4.5 | Statistical analysis

Our hypothesis for objective 1 is that there are no differences in the blink rates obtained using the generic camera-based system and the scientific-grade eye-tracker. For this reason, considering the characteristics of the traditional null hypothesis statistical testing (NHST), using this approach would inflate the type 2 error, that is, the likelihood of finding a false negative. This is because the likelihood of the null hypothesis H_0 being accepted (and the alternative hypothesis H_1 being rejected) is higher than that of it being rejected (and H_1 being accepted). For this reason, a Bayesian analysis approach is preferred over NHST. Bayesian analysis set up two competing models, one in favour of the null hypothesis and the other in favour of the alternative hypothesis, and estimate which of the two models is more likely to generate the data at hand. In detail, the Bayesian approach transforms the *p*-values into direct evidence against the null hypotheses [45]. The Bayes Factor (BF), which is used to determine the likelihood of the data under either the null or the alternative hypotheses is calculated as the ratio between the marginal likelihood of the null model and that of the alternative model [46]. A BF equal to X indicates that the data is X times more likely under the alternative hypotheses than under the null hypothesis. For example, a BF of 10 indicates that the given data is 10 times likelier under H_1, whereas a BF $= 0.01$ indicates that the same data is 10 times likelier under H_0. According to Dienes [47], BF varies between 0 and infinity. The bigger the BF (with BF > 1), the stronger the evidence in support of the alternative hypotheses. Likewise, the smaller the BF (with BF < 1), the stronger the evidence in support of the null hypotheses. BF $= 1$ indicate that the data is not supportive of either model. In short, unlike NHST which only yields a binary outcome (accept/reject H_0), BF analysis allow for three separate conclusions (evidence in support of H_0, evidence in support of H_1, and insensitive evidence) as well as provides information on the strength of the evidence. Bayesian test equivalents of general linear tests were used to analyse data for objectives 1 and 2 [46]. Data processing and analyses were conducted using R (version 4.1.0) and RStudio (version 2023.03.0; [48]). The *tidyverse* (version 2.0) and *BayesFactor* (version 9.12) libraries were adopted for data processing and Bayesian analyses, respectively. The data used to support the findings of this study have been deposited in the University of Windsor RedCap repository which is available at the following link: https://redcap.uwindsor.ca/surveys/?__file=LLSaQPkjLrofM3uCvkIpYXfz33Q2UsnMybjzqjcegVAkQyroKcyLVcoNXDoDV8J5fPdAJ2Bk9tep8txbmEmCIgBnNfhcidx3E6JM.

3 | RESULTS

Results are presented by objectives with objective 1 investigating the accuracy of the generic camera-based system through comparing the resulting blink rate with that obtained using the eye-tracker, and objective 2 investigating the accuracy of the generic camera-based system in detecting increasing levels of cognitive load.

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3.1 | Objective 1. Accuracy of the generic camera-based blink detection system

Repeated-measure Bayesian analysis of variance models with blink rate as dependent measure, and participant ID as random factor were set up to test objective 1. A model with blink detector (2 levels: eye-tracker, generic camera-based system) as the independent factor was set up to investigate whether blink rate differed across the two systems. A BF of 0.18 was found indicating evidence in support of the null hypothesis that blink rates obtained using the two systems were not different. A model with blink detector and cognitive task difficulty (3 levels: easy, medium, hard) was set up to investigate the interaction between the two factors. A BF of 0.03 was found suggesting strong evidence in support of the null hypothesis that no interaction was present. Table 2 shows blink rates across the two systems and three cognitive task difficulty conditions.

3.2 | Objective 2. Accuracy of the generic camera-based blink detection system in detecting increasing levels of cognitive load

A repeated-measure Bayesian analysis of variance model was set up with participant ID as random factor, cognitive task demand (3 levels: easy, medium, hard) as the independent factor, and blink rate obtained through the generic camera-based system as the dependent measure. A BF of 0.22 was found indicating evidence that the blink rate recorded using the generic camera-based system did not change with cognitive task demand. To ensure that the increasing level of difficulty of the cognitive task in fact induced greater cognitive load, separate repeated-measure Bayesian analysis of variance models were run with blink rate obtained through the eye-tracker as the dependent measure. A BF of 40.65 revealed that, when recorded using the eye-tracker, blink rate in fact increased under conditions of greater cognitive task demand (Table 3). Similar analyses run on response times in the single stimulus detection task and self-reported mental demand ratings both revealed consistent results showing very strong evidence that the increasing cognitive task demand increased both response times, $BF = 1.15 \times 10^{15}$, and self-reported ratings of mental demand, $BF = 2.6 \times 10^{84}$. Table 2 shows response times and cognitive load ratings by condition.

4 | DISCUSSION

Our first objective aimed to test the accuracy of the generic camera-based blink detection system by comparing its resulting blink rate with that obtained using a scientific-grade eye-tracker. Bayesian analyses showed evidence that no differences were present between the two systems. On average, only a small discrepancy of 1.54 blinks per minute was observed between the two systems across the three experimental conditions. This is a key finding in that it shows the potential for generic camera-based systems that use footage from ubiquitous cameras to serve as a feasible solution for tracking blink rate. Dewi et al. [24] and Pandey and Muppalaneni [27] attempted to validate similar video-based systems for tracking eye blinks but failed to do so as, in addition to only using short videos recorded on individual participants, their results were not validated using established ground-truth methodologies. Our findings add to the existing literature posing generic camera-based systems as a plausible future alternative to scientific-grade eye-trackers.

Our second objective aimed to investigate using the generic camera-based blink detection system to track changes in cognitive load. Analysis showed that, when the output from the generic camera-based sysytem was used, no differences in blink rate were observed under greater cognitive task demand. This despite the fact that, consistently with the current literature [5, 21, 49, 50], slower response times to the detection task, higher self-reported ratings and, more importantly, a higher blink rate obtained using the eye-tracker were observed as the cognitive task became more difficult. These results seemingly conflict with our findings for objective 1. We posit that, overall, while the output of our generic camera-based system was consistent with that of a scientific-grade eye-tracker's, its sensitivity in tracking changes in cognitive load was in fact less than that of its counterpart's. Note that a difference in blink rate of 2 blink/minute was noted between the easy and hard task conditions for the generic camera-based system, compared to an increase in 6 blink/minute for its counterpart. We argue that this could be the result of the chosen approach for eye blink detection and that the system's accuracy could be improved by further revising the characteristics of the adaptive threshold (e.g. the duration of the time window or how the threshold is calculated). The possible interfering role of camera characteristics (e.g. sampling rate, noise) also cannot be excluded. It is also possible that the rise in cognitive task demand experienced in the hard condition was insufficient or the characteristics of the

TABLE 2 Mean blink rate (in number of blinks per minute) and standard error (SE) of blink rate by system (eye-tracker and generic camera-based) in the three cognitive task difficulty conditions (easy, medium, hard).

	Cognitive task difficulty					
	Easy		Medium		Hard	
System	Mean	SE	Mean	SE	Mean	SE
Eye-tracker	19.07	2.48	22.10	3.42	25.81	3.63
Generic camera-based	22.29	1.91	22.09	2.38	24.40	2.14

TABLE 3 Response times (RT in seconds) and standard error (SE) of RT, self-reported cognitive load ratings and SE of ratings in the three cognitive task difficulty conditions (easy, medium, hard).

	Cognitive task difficulty					
	Easy		Medium		Hard	
Measure	Mean	SE	Mean	SE	Mean	SE
RT	0.42	0.02	0.49	0.02	0.72	0.03
Ratings	21.60	1.51	30.00	1.48	58.40	1.53

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chosen task were inadequate to induce meaningful changes in the blink rate obtained through the generic camera-based system. Our future research will address these issues.

Altogether, our findings show promise. Our study adds to the literature using less intrusive means for the assessment of oculomotor behaviours. While the vast majority of the research use scientific-grade eye-trackers for recording blink rate [51, 52], this methodology comes with severe limitations when employed outside traditional laboratory settings. For once, even when using more portable solutions, their associated costs (e.g. monetary, expertise) limit its adoption in everyday settings [53–55]. With this in mind, the current study has some clear caveats. Participants were instructed to complete a mental task while staring at a computer screen from a set distance. While this was necessary in our study, it may not reflect the reality in the workplace. For this reason, future research should investigate using more realistic tasks, and explore the effect that sudden head and eye movements have on the accuracy of the proposed approach.

Our data pose generic camera-based systems as a potential solution to this issue, especially in workplace environments where generic cameras are readily available. For example, in office or home office settings wherein the rate of mental fatigue and burnout increased during the COVID-19 pandemic as a direct result of the sustained engagement in videoconferencing [56, 57], it is plausible that camera-based solutions may be employed for monitoring and proactively detecting cognitive overload before its onset. Likewise, in manufacturing wherein psychological are responsible for a higher risk of work-related injuries [3, 58], it is possible that inexpensive solutions like the one proposed here may allow for the early detection of high cognitive load in workers, especially for the jobs requiring completing repetitive workstation tasks. In telehealth, where both the user and the healthcare provider are at a high risk of experiencing mental stress due to information overload, technological barriers, or distractions [59, 60], leveraging camera technology that is already part of telehealth's delivery methods may be a possible solution to reduce the risk of cognitive overload.

Notwithstanding the potential applications and benefits of the proposed system, we recognise that, because of its current limitations, further research is required to validate its use in the real-world. While similar systems also promise accurate camera-based fatigue and distraction detection [61, 62], their ability to detect dynamic fluctuations in the user state in the field is still unproven.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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