

Experimental Evaluation of a Heart Rate–Based Warning System for Driver Sleepiness Detection

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ABSTRACT

Driver sleepiness is a major contributor to road accidents, making early detection and intervention essential for improving driving safety. This study presents an experimental evaluation of a heart rate (HR)–based warning system designed to identify physiological indicators of drowsiness and provide timely alerts to drivers. Fifteen licensed drivers (aged 21–26) completed four 30-minute sessions in a monotonous driving simulator while HR was continuously measured using a photoplethysmography (PPG) sensor and subjective sleepiness was assessed using the Karolinska Sleepiness Scale (KSS). Results showed a progressive decline in HR across baseline sessions (S1–S3: 83.70 → 76.05 → 70.17 bpm), corresponding with increasing sleepiness (KSS: 5.86 → 6.16 → 6.27). When the HR-based warning system was activated in Session 4, HR increased to 75.71 bpm while KSS decreased slightly to 6.06, indicating a partial reversal of drowsiness. Repeated-measures ANOVA confirmed significant effects of session on both HR and KSS ($p < .05$). These findings demonstrate that HR monitoring can effectively detect physiological changes associated with driver sleepiness and that a threshold-based auditory alert can elicit an acute arousal response. While results show promise, findings are based on a simulator study and validation with larger, real-world datasets is recommended.

Keywords: Driver sleepiness; driver heart rate; warning system; Karolinska Sleepiness Scale; drowsiness

INTRODUCTION

Driver sleepiness is a critical contributor to road traffic accidents, leading to reduced vigilance, slower reaction times, and impaired decision-making. International statistics estimate that 10–30% of severe road crashes are associated with drowsiness, particularly during late-night driving or on monotonous highways (Philip & Åkerstedt 2006; Connor et al. 2002). In Malaysia and many other countries, fatigue-related crashes remain a persistent safety concern, underscoring the need for reliable, early-stage detection and effective intervention strategies.

Traditionally, driver drowsiness has been assessed using observable behavioural indicators such as eyelid closure (PERCLOS), head nodding, steering variability, and lane deviation. Although these measures can be

informative, they often identify fatigue only after driving performance has already deteriorated (Wierwille & Ellsworth 1994; Dinges et al. 1998). Their accuracy can also be affected by lighting conditions, environmental factors, and individual differences, limiting their reliability in real-world settings.

Physiological monitoring offers a more direct and earlier signal of declining alertness. Electroencephalography (EEG) is widely regarded as the gold standard for detecting neural changes associated with drowsiness (Makeig & Jung, 1996; Jap et al. 2009), but its intrusiveness and complexity limit its suitability for everyday driving. In contrast, cardiovascular markers such as heart rate (HR) and heart rate variability (HRV) are less intrusive and have demonstrated strong correlations with fatigue, reflecting a shift toward parasympathetic dominance as alertness decreases (Ahn et al. 2016; Vicente et al. 2016).

Recent advancements in wearable photoplethysmography (PPG) sensors have further increased the feasibility of HR-based monitoring. Lightweight, non-invasive PPG devices enable continuous cardiovascular measurement and can be seamlessly integrated into vehicles or personal wearables. Prior studies have demonstrated the potential of HR- and HRV-based drowsiness detection, including approaches validated against EEG-based sleep scoring (Fujiwara et al. 2019). Compared with behavioral indicators, physiological monitoring generally detects drowsiness earlier, making it more suitable for proactive fatigue management.

Recent studies have expanded the understanding of physiological and vehicle-based drowsiness detection. Fujiwara et al. (2019) demonstrated that HRV-based detection can be validated against EEG-based sleep scoring, while Kundinger et al. (2020) showed the feasibility of machine-learning classification using HRV from a wrist-worn wearable device. Lee et al. (2019) further distinguished drowsy and awake states using HRV derived from wearable ECG and PPG sensors. More recently, AlArnaout et al. (2025) reported that wearable-derived HRV features combined with machine-learning models can support driver-drowsiness detection. Vehicle-based measures can provide complementary information; Arefnezhad et al. (2019) demonstrated drowsiness classification using steering-wheel data. Together, these studies support physiological monitoring, potentially combined with vehicle-based measures, for practical driver-state detection.

Although HR and HRV have been widely investigated for drowsiness detection, their implementation is not always straightforward in a low-cost embedded system. Several approaches derive spectral or frequency-domain HRV measures, while others use classification algorithms that require additional data processing. Such approaches can provide useful information about driver state, but they also increase the computational requirements of the monitoring system. For an in-vehicle warning device intended to operate continuously and respond quickly, a simpler physiological indicator may therefore be advantageous. The present study addresses this gap by evaluating a simplified, low-cost drowsiness-warning system that uses a PPG-based HR sensor integrated with a microcontroller and a real-time threshold-triggered alert mechanism. Unlike HRV- or ML-based systems, this approach detects physiological decline instantaneously and triggers an immediate auditory countermeasure without complex processing.

Furthermore, this study validates the system using a controlled driving-simulator protocol designed to assess both physiological (HR) and subjective (KSS) indicators of sleepiness. By examining whether HR decline

corresponds to increases in subjective sleepiness, and whether an auditory alarm triggered at a low HR threshold can reverse this decline, the study provides a practical evaluation of the system's effectiveness. These contributions distinguish the present work from earlier HR- and HRV-based research and highlight its potential for scalable, cost-effective, and rapid-response driver fatigue monitoring.

METHODOLOGY

PARTICIPANTS

Fifteen licensed drivers (11 male, 4 female) aged between 21 and 26 years ($M = 23.2$, $SD = 1.4$) voluntarily participated in this study. Table 1 shows participant demographics. All participants reported normal or corrected-to-normal vision and no history of cardiovascular or sleep-related disorders. They were instructed to abstain from caffeine and alcohol for at least 12 hours prior to the experiment and to maintain regular sleep on the night before testing. Written informed consent was obtained, and the study protocol was approved by the Universiti Teknologi MARA Ethics Committee (Ref: 800-KPK (PI 1/1/34)-10).

TABLE 1. Participant Demographics

Variable	Value
Sample size (n)	15
Age range (years)	21–26
Mean age $\pm$ SD	23.2 ± 1.4
Gender	11 male (73.3%), 4 female (26.7%)
Vision status	Normal or corrected-to-normal
Health exclusion criteria	No cardiovascular or sleep disorders

APPARATUS AND MATERIALS

A fixed-base driving simulator was used to replicate monotonous highway driving conditions. The scenario featured a straight, dual-lane highway with minimal traffic and uniform speed requirements to induce drowsiness. Drivers operated the simulator using a standard steering wheel, accelerator, and brake pedal. The monotonous driving scenario was implemented using a Unity3D fixed-base driving simulator (Figure 1), designed with a dual-lane straight highway and minimal traffic to induce driver sleepiness.



FIGURE 1. Unity3D driving simulator used to replicate monotonous dual-lane highway driving conditions for inducing sleepiness.

Physiological data were collected using a MAX30100 photoplethysmography (PPG) sensor, attached to the participant's index finger, to measure heart rate (HR) continuously. The sensor was connected to a custom microcontroller system with real-time processing capability. The HR sensor was connected to an Arduino-based warning system (Figure 3), which processed incoming HR signals in real time. The Arduino code (FIGURE 4) was programmed with a threshold HR value of 70 bpm, below which the auditory warning buzzer was triggered.

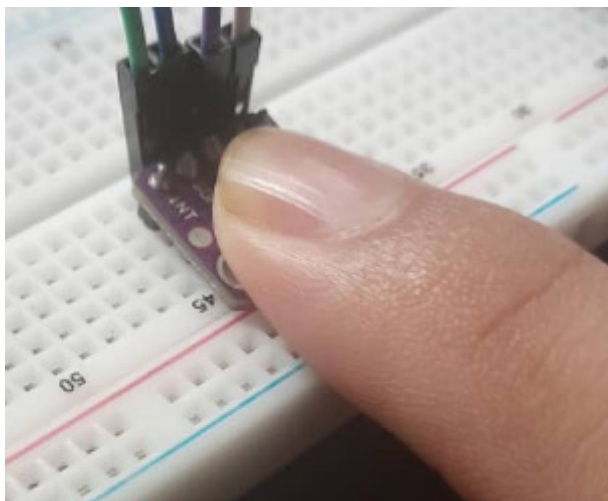


FIGURE 2. Placement of the MAX30100 photoplethysmography (PPG) sensor on the participant's index finger for continuous heart rate measurement.

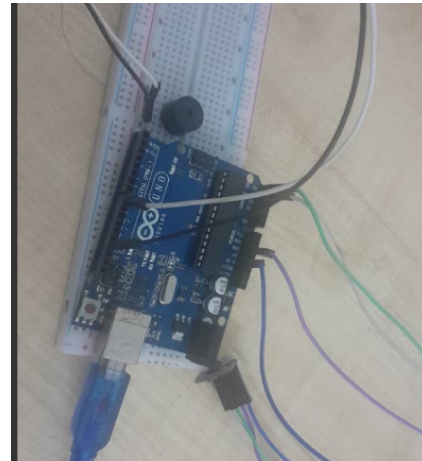


FIGURE 3. Arduino-based heart rate detection and warning system used for real-time monitoring and triggering of auditory alerts.

```
const float SLEEPINESS_THRESHOLD = 70.0;
bool alarmActive = false;
bool buzzerState = false;
```

FIGURE 4. Arduino code segment illustrating the heart rate threshold (70 bpm) used to activate the drowsiness warning buzzer.

Subjective sleepiness was assessed with the Karolinska Sleepiness Scale (KSS), a validated 9-point scale ranging from 1 ("extremely alert") to 9 ("very sleepy, fighting sleep") administered at one-minute intervals during each session. To complement physiological monitoring, the Driver's Behaviour Sleepiness Scale (DBSS) with integrated KSS levels was used for subjective assessment, as shown in Table 2.

TABLE 2. Driver's Behaviour Sleepiness Scale (DBSS) integrated with the Karolinska Sleepiness Scale (KSS), used for subjective assessment of sleepiness

Level of KSS	Criteria of Drowsiness	Behaviour	Explanation
4.0	Alert	Change driving style	The driver changes driving style from using both hands to one hand or from one hand to both hands.
4.0	Alert	Blinking $\leq$ 10 times per minute while driving	The driver blinks 10 times or fewer per minute.
6.5	Some signs of sleepiness	Blinking $>$ 10 times per minute while driving	The driver blinks more than 10 times per minute.

continue...

...cont.

7.0	Sleepy, but making effort to stay awake	Yawning two or more times for >5 seconds	The driver yawns two times for more than five seconds.
8.0	Closing eyes or falling asleep	Having conversation or singing	The driver starts talking with others or singing while driving to stay awake.
8.5	Sleepy, some effort to keep awake	Stretching body parts	The driver stretches their body, moves their head left to right, or inclines their body forward.

EXPERIMENTAL DESIGN

A within-subjects design was employed. Each participant completed four driving sessions (S1–S4), each lasting 30 minutes.

1. Session 1 (S1): Baseline driving without any intervention.
2. Session 2 (S2): Repeated driving under identical conditions.
3. Session 3 (S3): Continued driving to further induce drowsiness.
4. Session 4 (S4): Driving with the HR-based warning system activated. An auditory buzzer alarm was triggered when HR fell below a threshold of 70 bpm. The overall experimental setup, including simulator, sensor, and auditory alarm system, is presented in Figure 5.



FIGURE 5. Complete experimental setup showing simulator, HR sensor system, and auditory warning mechanism.

PROCEDURE

Participants were first briefed about the study and fitted with the PPG sensor. They then performed four consecutive sessions with short rest breaks in between to reduce simulator discomfort while maintaining drowsiness buildup. During each session, HR was continuously monitored, and KSS ratings were verbally reported once every minute.

In S4, whenever the system detected HR below 70 bpm, the Arduino buzzer emitted a 70 dB auditory alarm for 3 seconds. Participants were instructed to continue driving normally upon hearing the alarm. Figure 6 provides a flowchart of the experimental procedure, highlighting the sequence of driving sessions, rest intervals, and warning system activation.

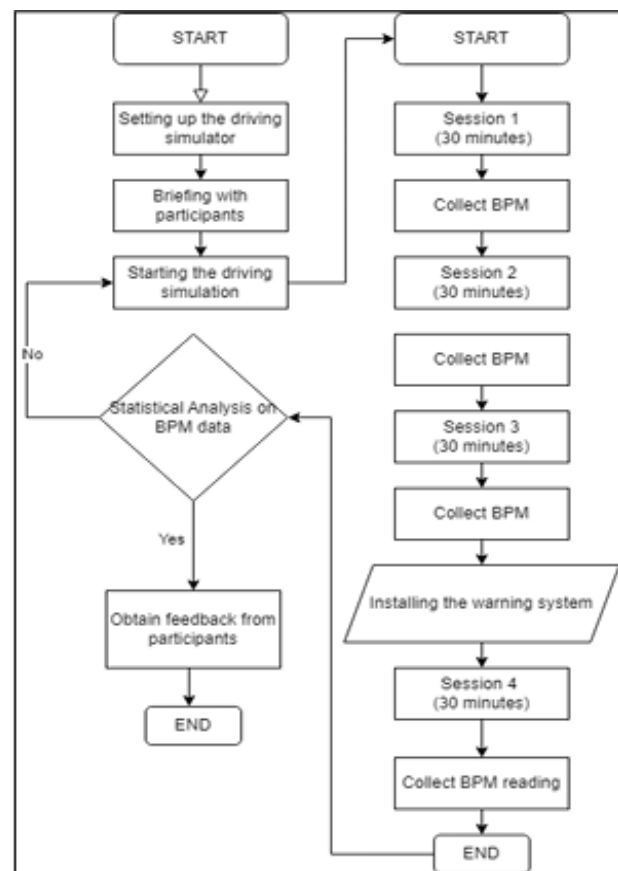


FIGURE 6. Flowchart of the experimental procedure detailing baseline sessions, rest intervals, and activation of the HR-based warning system.

DATA COLLECTION

Physiological data: HR values (beats per minute) were sampled once per second and averaged over one-minute

intervals. Each 30-minute session thus yielded 30 HR data points per participant.

Subjective data: KSS ratings were recorded every minute, yielding 30 data points per session per participant.

DATA ANALYSIS

Data was analyzed using IBM SPSS Statistics version 27. Repeated-measures ANOVA with Greenhouse–Geisser correction was applied where necessary, and Bonferroni-adjusted post hoc comparisons were performed. Pearson correlation analysis was conducted to evaluate the relationship between HR and KSS.

The analysis was performed at the session level to examine changes across repeated exposure to the monotonous driving task and the subsequent warning condition. HR and KSS were treated as complementary measures: HR represented the physiological response, whereas KSS represented the participant's perceived level of sleepiness. This combination was selected because a change in a physiological signal alone does not necessarily indicate that the driver experiences a corresponding change

in subjective alertness. Repeated-measures analysis was appropriate because the same participants completed all four experimental conditions, allowing within-participant changes across sessions to be evaluated.

RESULTS AND DISCUSSION

HEART RATE (HR)

Mean HR declined progressively across the first three sessions, with values of 83.70 bpm (S1), 76.05 bpm (S2), and 70.17 bpm (S3). When the HR-based warning system was activated in Session 4, mean HR increased to 75.71 bpm (Figure 7). A repeated-measures ANOVA revealed a significant main effect of session on HR, $F(1.62, 22.68) = 140.86$, $p < .001$, $\eta^2 = .91$. Post hoc comparisons confirmed significant decreases from S1 to S2 and S2 to S3 ($p < .01$), followed by a significant increase from S3 to S4 ($p < .01$). These results indicate that HR declined with increasing drowsiness but rebounded when the warning system was applied.

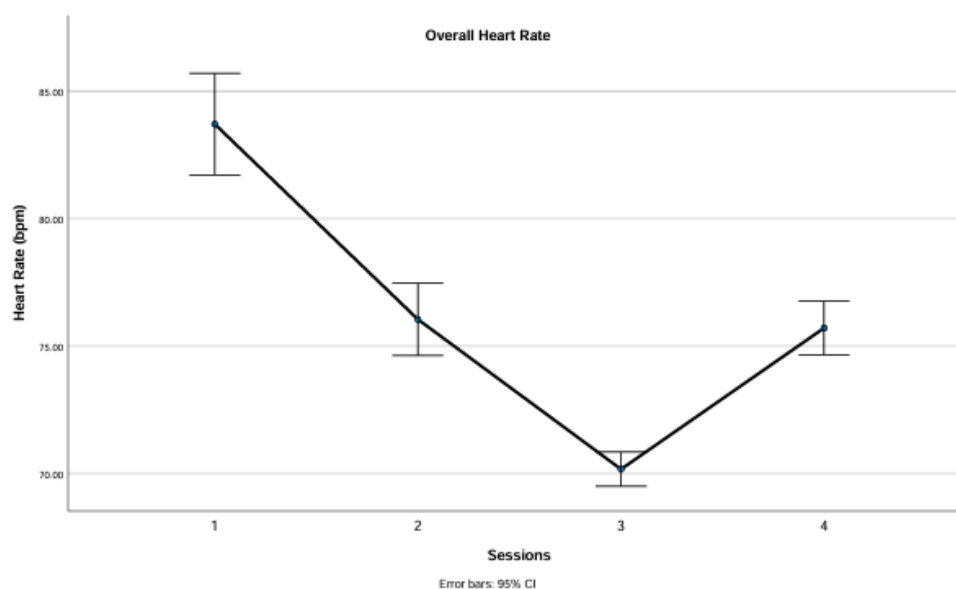


FIGURE 7. Mean heart rate (HR) values across sessions (S1–S4). Error bars represent 95% confidence intervals.

KAROLINSKA SLEEPINESS SCALE (KSS)

Subjective sleepiness followed a similar pattern. KSS scores increased from 5.86 (S1) to 6.16 (S2) and 6.27 (S3), indicating progressive fatigue, then decreased slightly to 6.06 in S4 after the HR-triggered auditory warnings (Figure

8). ANOVA results showed a significant session effect, $F(3, 42) = 5.23$, $p < .01$, $\eta^2 = .27$. Post hoc tests revealed significant increases from S1 to S3 ($p < .05$), and while the reduction from S3 to S4 was modest, it was statistically significant ($p < .05$). Together, these findings show that the warning system partially reversed subjective sleepiness.

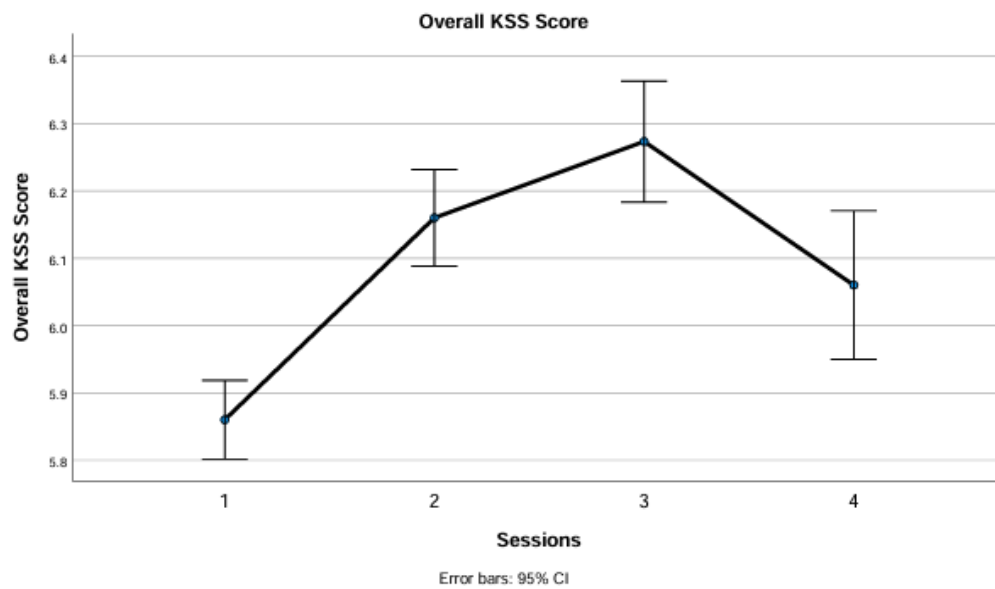


FIGURE 8. Mean Karolinska Sleepiness Scale (KSS) scores across sessions (S1–S4). Error bars represent 95% confidence intervals.

Table 3 summarizes the mean Heart Rate (HR) and Karolinska Sleepiness Scale (KSS) scores across sessions.

TABLE 3. Summary of Mean Heart Rate (HR) and Karolinska Sleepiness Scale (KSS) Scores Across Sessions

Session	Mean HR (bpm)	SD (HR)	Mean KSS	SD (KSS)
S1 – Baseline	83.70	3.0	5.86	0.30
S2 – Repetition	76.05	2.5	6.16	0.25
S3 – Elevated Fatigue	70.17	1.8	6.27	0.35
S4 – Warning Activated	75.71	2.2	6.06	0.28

CORRELATION BETWEEN HR AND SUBJECTIVE SLEEPINESS

A Pearson correlation analysis between mean HR and mean KSS scores demonstrated a significant negative association, $r = -0.72, p < .001$. Lower HR was strongly linked to higher perceived sleepiness, supporting the reliability of HR as an objective physiological indicator of drowsiness and reinforcing its value for early detection.

PHYSIOLOGICAL INTERPRETATION

The progressive HR decline observed across S1–S3 aligns with well-established autonomic nervous system changes during fatigue. As monotonous driving continues, cortical activation decreases, leading to a shift toward parasympathetic nervous system dominance, which slows

heart rate and reduces metabolic arousal. Ahn et al. (2016) similarly demonstrated that sleep deprivation increases parasympathetic activity while suppressing sympathetic modulation. Recent work (Liu et al. 2021; Zhang et al. 2023) confirms that vagal activation during fatigue reliably manifests as HR and HRV reductions. The HR rebound in S4 indicates that the auditory alert elicited an acute arousal response, activating sympathetic pathways and momentarily restoring alertness.

Importantly, the physiological rebound was stronger than the subjective improvement in KSS, suggesting that autonomic arousal can occur before drivers consciously perceive changes in their sleepiness level.

COMPARISON WITH EXISTING HR/HRV-BASED SYSTEMS

Previous studies have shown that HR and HRV can provide useful information on changes in driver alertness. However, the processing required differs considerably between methods. HRV approaches commonly derive time- or frequency-domain parameters, and more recent detection systems may combine several physiological variables within a classification model. These methods can improve the description of driver state, but their additional processing requirements may be less suitable for a simple embedded warning device. The present study therefore examines whether a direct change in HR can be used as a practical trigger for an immediate warning.

In contrast, the present work introduces a simplified, microcontroller-based HR threshold mechanism that:

1. detects physiological decline instantly,
2. triggers an immediate countermeasure with minimal computation, and
3. is easily deployable in low-cost hardware or wearable devices.

This distinguishes the system from earlier HRV-based and ML-based approaches and supports its relevance for rapid-response, scalable fatigue countermeasures.

However, the threshold-only approach is less individualized. Resting HR varies considerably across drivers, and recent studies highlight the importance of personalised baselines and adaptive thresholds. Future work should incorporate adaptive algorithms that adjust threshold values to individual physiology.

PRACTICAL ENGINEERING IMPLICATIONS

From a systems-engineering perspective, the proposed HR-based warning system offers several advantages:

1. Low-cost PPG sensors and microcontroller integration enable deployment in older vehicles, fleet trucks, and motorcycles.
2. Physiological detection provides earlier warning than behavioural indicators such as lane deviation.
3. Real-time threshold detection reduces processing overhead, allowing use in resource-limited embedded platforms.

To further enhance robustness and reduce habituation, future systems should combine auditory alarms with multimodal alerts (e.g., vibration, LED indicators). Integrating physiological signals with Advanced Driver Assistance Systems (ADAS) would also enable coordinated safety interventions such as lane-keeping assist or adaptive cruise control activation during fatigue episodes.

The observed pattern also has implications for the way a warning threshold should be interpreted. A value of 70 bpm was used in the present prototype as an operational trigger rather than as a universal physiological boundary for drowsiness. Heart rate is influenced by age, physical fitness, emotional state, medication, temperature, posture, and individual resting cardiovascular characteristics. Consequently, the usefulness of the proposed system lies primarily in demonstrating that a simple HR signal can be processed in real time and linked directly to an intervention. For practical deployment, calibration against an individual driver's baseline would be preferable to applying the same absolute threshold to every user.

The difference between the HR and KSS responses after warning activation is also noteworthy. In S4, the mean HR increased from the S3 value of 70.17 bpm to 75.71 bpm, whereas the mean KSS decreased only from 6.27 to 6.06. This suggests that the auditory stimulus produced a clearer immediate cardiovascular response than a change in the participants' subjective perception of sleepiness. The result should not be interpreted as evidence that a short alarm eliminates fatigue. Rather, it indicates a temporary arousal response that may provide the driver with an additional opportunity to recognize declining alertness and take appropriate safety action, such as stopping for rest.

For transport applications, this distinction is important because a warning system should support, rather than replace, fatigue-management practices. The prototype is intended as an early warning aid and not as a means of extending driving while sleepy. In fleet operations, physiological warning information could eventually complement existing controls such as work-rest scheduling, driver education, journey planning, and organizational fatigue-management procedures. The relatively simple hardware architecture evaluated in this study may be useful where cost and processing capacity are important constraints, provided that subsequent validation establishes acceptable sensitivity, specificity, and robustness under real driving conditions. The present findings should also be considered in relation to implementation reliability. PPG is attractive for a prototype because it is non-invasive and inexpensive, but signal quality can be affected by finger movement, sensor contact, and motion artefacts. These factors are likely to be more pronounced in an actual vehicle than in a fixed-base simulator. A production system would therefore require signal-quality checks and an appropriate strategy for handling missing or unreliable readings before a warning is issued. Alternative sensor locations or wearable configurations may also improve usability. Evaluating these practical factors is necessary before the proposed concept can be translated from an experimental prototype into a dependable driver-monitoring device.

LIMITATIONS AND FUTURE WORK

The study has several limitations. The small sample size ($n = 15$) and narrow age range restrict generalizability. Simulator-based findings may not fully reflect real-world driving, where environmental and cognitive demands vary. Only auditory alerts were tested; tactile or visual modalities may produce stronger or more sustained arousal effects. Future research should involve larger, more diverse populations, extended driving durations, adaptive HR

thresholding, and multimodal detection combining HR/HRV with gaze, steering, or PERCLOS measures.

A further limitation concerns the fixed 70 bpm threshold. The threshold was suitable for evaluating the prototype logic in this experiment, but it cannot be assumed to represent the same level of sleepiness for all drivers. The study also did not evaluate false alarms, missed detections, or the sensitivity and specificity of the threshold against an independent physiological reference measure such as EEG. In addition, repeated exposure across four consecutive sessions may introduce order and carry-over effects. These issues should be addressed in subsequent validation using individual baseline calibration, counterbalanced or extended protocols, and performance measures that quantify detection accuracy.

CONCLUSION

This study demonstrated that heart rate monitoring is a viable method for detecting driver sleepiness and that a threshold-based auditory warning system can partially reverse both physiological and subjective indicators of fatigue. The progressive decline in HR and rise in KSS during baseline sessions confirm the sensitivity of cardiovascular responses to drowsiness, while the HR rebound observed during the warning-activated session indicates that simple, real-time alerts can elicit an immediate arousal effect.

Beyond establishing feasibility, the findings highlight several opportunities for system refinement. A fixed HR threshold, although effective for generating timely alerts, does not account for inter-individual variability in baseline physiology. Future systems should therefore incorporate adaptive thresholds that learn each driver's typical HR profile. In addition, multimodal alerting combining auditory, tactile, and visual cues may enhance user responsiveness and reduce habituation to repeated warnings.

From an engineering standpoint, the system's low computational demand and straightforward implementation make it suitable for integration into cost-effective automotive or wearable platforms. Its practicality can be further enhanced by linking physiological monitoring with Advanced Driver Assistance Systems (ADAS), enabling coordinated safety interventions such as lane-keeping assistance or adaptive cruise control when fatigue is detected.

To ensure real-world applicability, future research should evaluate adaptive thresholding, multimodal alerting, and sensor fusion with steering, gaze, or other behavioural metrics, and validate system performance under extended driving durations and diverse operational conditions.

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DECLARATION OF COMPETING INTEREST

None.

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