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Mental Workload in Truck Driving: A NASA-TLX and HRV-Based Comparison Across Day-Night and Rural-Urban Conditions

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Abstract: Truck-involved accidents often result in severe consequences due to the vehicle's size and mass, making driver fatigue and cognitive overload critical risk factors. Mental workload reflects real-time cognitive demands during driving, where excessive levels accelerate fatigue, impair response time, and increase accident risk. This research investigates the effects of four driving scenarios (rural daytime, rural nighttime, urban daytime, urban nighttime) on the mental workload of 50 professional male truck drivers, using NASA Task Load Index (NASA-TLX) assessment and Heart Rate Variability (HRV) metrics (aLF, aHF, ln-aLF, ln-aHF, nLF, nHF, and HR in bpm). Performance was measured through response time, hit rate, and error rate. The NASA-TLX results indicate a proportional increase in mental workload from rural daytime to urban nighttime. Mental Demand ($p = 0.025$) and Temporal Demand ($p = 0.047$) are significantly higher in urban nighttime compared to rural daytime, while other dimensions, though not significant, show a general pattern of increasing mean scores, with Performance showing the opposite pattern. Heart rate (bpm) significantly increases, and nLF power shows a significant reduction during urban nighttime scenario compared to rural daytime ($p < 0.03$), indicating increased mental workload. Two-way ANOVA further revealed that road condition (urban vs. rural) significantly affected HRV indices (nLF, nHF, and HR), while driving time (nighttime vs. daytime) significantly elevated Mental Demand and Frustration, highlighting the distinct contribution of environmental and temporal factors to driver workload. Significantly, response times were slowest in rural nighttime scenarios, hit rates were higher at night than during the day, and error rate peaked in urban nighttime driving, suggesting that reduced visibility and traffic density contribute to increased mental workload. These findings provide a more structured and advanced methods for measuring truck drivers' mental workload, benefiting company management in optimizing driver performance and safety.

Keywords: driver performance.; Heart Rate Variability; mental workload; NASA-TLX; truck drivers

1. Introduction

Road transport serves as the primary backbone for freight distribution in many regions[1]. As the largest economy in ASEAN contributing approximately 36–40% of the region's total GDP and a strategically important maritime nation with over 17,000 islands, Indonesia's freight transport remains heavily dominated by road-based trucking due to the limited integration and capacity of its

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sea and rail logistics networks. Trucking companies in Indonesia serve as a critical pillar of the national economy, handling approximately 90% of the country's freight transport activities[2,3]. This overwhelming reliance on road-based logistics reflects not only the geographic structure of the archipelago, where last-mile connectivity is often best achieved via land, but also the limited development and integration of alternative freight modes such as rail and maritime.

Truck sales in Indonesia grew at an annualized rate of 10% from 2000 to 2017 [3] and according to Statistics Indonesia (BPS)[4], the number of freight vehicles increased from approximately 5.3 million units in 2017 to over 5.7 million units in 2022, reflecting steady growth in Indonesia's truck population in line with rising logistics demand. Ironically, despite the essential role of trucks in freight transport, their growing numbers in Indonesia correlate with increased road accidents[5]. In 2021, 80% of traffic fatalities in Indonesia involved motorcycle users, while heavy trucks were recorded as the second-largest vehicle group after passenger cars, with 5.5 million units—equivalent to nearly 30% of total passenger car registrations. Truck-type vehicles are significantly associated with fatal crashes on toll roads, with accident cases involving large trucks with two axles accounting for approximately 30% of total fatalities[6]. Road traffic crashes resulted in economic losses amounting to Rp 200 billion, reflecting a 21.55% increase from the previous period[7]. Globally, heavy truck-related fatalities have also surged. In the United States, 5,700 fatal crashes involving heavy trucks were recorded in 2022—an increase of 18% from 2020 and 48% over the past decade. In Europe, fatal truck-involved crashes ranked third after those involving cars and pedestrians, with 403 motorcyclist occupants affected[8]. In Indonesia, the National Transportation Safety Committee (KNKT) has urged the National Research and Innovation Agency (BRIN) to initiate targeted studies on motorcyclist safety strategies, due to the growing frequency of fatal collisions between freight trucks and motorcycles[9]. Between January and November 2024, 17,280 truck-related accidents were reported nationwide[10]. The Ministry of Transportation also reported that trucks consistently rank as the second most involved vehicle in road crashes after motorcycles, with only an 8–12% gap[11]. According to the World Health Organization[12,13], road traffic crashes cost countries up to 3% of their gross domestic product annually. Drowsy and distracted driving are among the leading causes of road accidents worldwide[14].

While many ASEAN countries have recently emphasized the promising role of autonomous technologies in reshaping road-based freight transport[15–17], Indonesia still appears to rely on conventional trucking. Although global players like Daimler AG and local firms such as J&T Express have started testing semi-autonomous and autonomous trucks, Indonesia still faces major challenges[18]. Poor road infrastructure[19], including congested urban roads and difficult rural routes, requires advanced systems that can handle complex environments[1,20]. Regulatory approval and concerns over job loss also make adoption more complicated. Therefore, truck drivers still play a pivotal role as frontline operators who ensure that goods are delivered safely, efficiently, and on time across vast and often challenging terrains. Their ability to make decisions and maintain situational awareness on the road is critical to ensuring the safety of freight transport.

Indonesia's trucking industry is highly competitive [21] and dominated by small-scale[3], often immature operators—most managing fewer than ten vehicles[2,21]. In such a competitive and underregulated environment, it is not uncommon for drivers to be pressured into working beyond reasonable limits to meet operational demands and client deadlines. This condition can lead to excessive mental workload[22], as drivers are forced to sustain prolonged attention, make rapid decisions under pressure, and navigate challenging road and traffic conditions. Such conditions elevate mental workload, impairing focus and decision-making, and increasing the risk of accidents.

Mental workload refers to the mental effort experienced by a person while performing a task, influenced by social, technical, organizational, and individual factors. It is a broad concept that includes mental strain and stress. Commonly, it is described as the gap between the demands of a task and the worker's available mental capacity to handle it[23]. Truck driving is a cognitively demanding profession that requires sustained attention, situational awareness, and rapid decision-making over prolonged periods[24]. Unlike passenger car drivers, truck drivers must continuously monitor their surroundings, control a vehicle with significant momentum, and adapt to varying road conditions, making them highly susceptible to mental workload accumulation[25]. These factors are critical because truck-involved crashes often result in severe consequences due to the vehicle's size and mass, leading to higher fatality rates compared to other road accidents[26,27]. In the field of human factors and transportation safety, mental workload assessment is gaining increasing recognition, as cognitive overload and fatigue are now understood to be as crucial as physical workload in influencing driving performance[26,28].

Traditionally, driver endurance and workload assessments have focused on physical strain, such as muscle fatigue, posture, and biomechanical stress[29,30]. However, modern transportation safety research emphasizes the importance of cognitive demands, as excessive mental workload can impair hazard perception, reaction time, and decision-making ability, leading to an increased risk of crashes and performance degradation[31–33]. Despite these advancements, in developing countries like Indonesia, mental workload assessments for professional truck drivers remain an underexplored topic, with durability and physical endurance still being the primary focus when evaluating truck driver performance and safety[26,34]. This research seeks to bridge this gap by highlighting how mental workload varies under different driving environments and time-of-day conditions and how it directly correlates with fatigue-induced errors and safety risks.

One of the key contributors to truck driver cognitive overload is the interaction between environmental complexity and time-of-day conditions[35]. Road and environmental characteristics have a significant impact on accident severity. Traffic safety strategies should be adapted to the specific context of rural or urban environments[36]. Lack of anticipation has been identified as a critical factor in traffic accidents[6], particularly among truck drivers operating under high workload conditions. The distinction between rural and urban driving conditions is essential for understanding the unique challenges faced by truck drivers. Urban environments typically involve higher traffic density, frequent stops, and complex road infrastructures, which require truck drivers to maintain higher levels of attention, hazard anticipation, and rapid decision-making [37,38]. This not only increases mental workload but also physiological stress, which can lead to fatigue and errors in judgment[39]. In contrast, rural environments are characterized by longer, monotonous stretches of road with fewer external stimuli, which can reduce immediate workload but increase the risk of cognitive underload, leading to fatigue-induced lapses in attention[40,41]. Such underload in rural settings, especially over extended periods, poses significant safety risks due to the potential for microsleeps and delayed hazard detection[42]. Both rural and urban settings present distinct cognitive demands that can affect driver alertness, performance, and safety, making it crucial to understand these differences when developing targeted safety strategies for truck drivers.

Similarly, time-of-day effects play a crucial role in mental workload fluctuations. Daytime driving generally benefits from higher visibility and reduced cognitive strain due to natural lighting, allowing drivers to better perceive road hazards[43]. A significant difference was found between light and dark conditions, where accidents occurring in dark conditions tend to result in more severe injuries[44]. Driving during the night poses significant challenges, including reduced peripheral vision, increased reaction time, and a higher reliance on artificial lighting[45]. Night driving is also associated with circadian rhythm disruptions, leading to increased drowsiness, slower cognitive processing, and greater susceptibility to fatigue-related errors. Research has shown that nighttime cognitive demand is amplified in urban settings, where glare from artificial lights, motion distractions, and dense traffic further tax attentional resources and elevate mental workload[46]. In contrast, rural nighttime driving, although less visually complex, increases the risk of microsleeps and delayed hazard detection due to the monotony and reduced external stimulation[42].

While previous studies have extensively examined mental workload in passenger car drivers, research specifically targeting professional truck drivers remains limited. Given the distinct cognitive challenges and safety-critical nature of truck driving, it is imperative to quantify mental workload fluctuations across different driving environments and time-of-day conditions. Traditional mental workload assessments often rely on subjective self-reports, such as the NASA Task Load Index (NASA-TLX), which captures perceived workload across six dimensions: mental demand, physical demand, temporal demand, effort, frustration, and performance[47]. However, objective physiological markers, such as Heart Rate Variability (HRV) metrics (absolute Low Frequency, absolute High Frequency, normalised Low Frequency, normalised High Frequency, Heart Rate in bpm, RMSSD), offer deeper insights into autonomic nervous system activity, enabling a more robust analysis of stress, cognitive demand, and fatigue accumulation[48].

This study aims to examine how mental workload varies in professional truck drivers by utilized four driving scenarios: rural daytime, rural nighttime, urban daytime, and urban nighttime. This study also provide a comprehensive understanding of how road conditions (rural and urban) and temporal factor or driving time (daytime and nighttime) influence mental workload in truck drivers by integrating subjective (NASA-TLX) and physiological measures of mental workload such as HRV. Furthermore, this research aims to highlight the critical need for mental workload assessments in truck driver safety policies, particularly in developing countries, where such considerations have not yet been fully integrated into transportation regulations and industry practices. The findings will contribute to evidence-based interventions aimed at reducing fatigue-related errors, optimizing workload management, and enhancing truck driver safety in real-world transportation settings.

2. Materials and Methods

2.1. Participants

A total of 50 professional male truck drivers (mean age = 38.68 years, SD = 8.67) participated in this study. All participants held a valid commercial driver's license (CDL) and had a minimum of one year of professional driving experience. To ensure homogeneity in the sample, only drivers with regular long-haul or freight transport experience were recruited. Participants were instructed to get sufficient sleep the night before experiment to mitigate the effects of fatigue.

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2.2. Experimental Setup

This study employs an experimental video-based approach to measure truck driver mental workload across four scenarios: rural daytime (RD), rural nighttime (RN), urban daytime (UD), and urban nighttime (UN), as well as to examine the main effects of road condition (rural vs urban) and driving time (daytime vs nighttime), along with their simultaneous interaction. The NASA-TLX questionnaire is used to measure subjective mental workload based on six dimensions: mental demand, physical demand, temporal demand, frustration, effort, and performance. A portable heart rate monitor sensor is worn by participants (see Figure 1) during both resting and simulation phases to measure objective mental workload using Heart Rate Variability (HRV) analysis. Driver performance, including response time, hit rate, and error rate, is also recorded.

Each participant undergoes a 5-minute adaptation session to familiarize themselves with the experimental setup. Each scenario lasts 15 minutes, with a 5-minute rest period between sessions to reduce fatigue and minimize carryover effects. Given the video-based nature of the study, a shorter duration was adopted to ensure that participants maintained focus and provided reliable responses, while minimizing uncontrolled factors such as fatigue or lapses of attention that could confound mental workload and performance. While professional driving particularly long-haul trucking, typically involves much longer durations, prior research demonstrates that shorter sessions can still yield valid measures of driving performance and cognitive workload. Čulík et al.[49] employed a 15-minute simulator scenario to evaluate driver reaction time, showing that such a duration is sufficient to capture meaningful performance indicators under controlled conditions. Similarly, Casutt et al.[50] used short-duration driving simulator sessions to assess the effects of divided attention and cognitive training on older drivers, highlighting that relevant workload and performance outcomes can be obtained within time-limited experimental designs. Accordingly, the use of a 15-minute session in this study is methodologically justified, as it enables reliable workload assessment while maintaining participant engagement and experimental control.

The driving scenarios are presented in a randomized order to minimize bias from the time of testing. Partial counterbalancing[51] was employed to ensure that participants were not exposed to the scenarios in a fixed sequence, thus minimizing the effects of the learning curve. During the simulation, participants are tasked with detecting the presence of motorcyclists on the screen. Immediately after completing each driving scenario, participants fill out the NASA-TLX questionnaire. Upon completion of all driving scenarios, participants are debriefed, and any additional observations are noted. As shown in Figure 2, the experimental videos were presented

Fig. 1: Polar heart rate monitor sensor worn by participant

on a monitor placed directly in front of the participant. Participants were instructed to press the space bar upon detecting motorcyclists appearing randomly from the rear right, rear left, or front of the truck, and to report detections to data collector person. The other monitor was operated solely by data collector to facilitate simultaneous tasks, including recording driving performance (response time, correct response, and error rate), monitoring heart rate data and participant's display, as well as administration task.

Although this setup is not based on a high-fidelity driving simulator, video-based designs[52,53] and single monitor[54] are accepted for assessing driver mental workload. In addition, previous research shows that display configuration has limited impact on mental workload. Saleem et al.[55] reported no significant NASA-TLX differences between single- and dual-monitor setups, and Park et al.[56] found no significant effect of display curvature to mental workload. These findings suggest that variations in display size, number, or curvature exert only marginal influence on mental workload. Thus, the use of a single monitor in this study is methodologically justified, as consistency and control of stimuli (standardization across all participants) are more critical than display form factors. Nevertheless, we acknowledge this as a limitation of the study, as an advanced driving simulator setup could further enhance ecological validity.

The driving scenarios were designed to provide realistic rural and urban environments while controlling for participant detection tasks, as shown in Figure 3. Each scenario included a combination of motorcycle stimuli and empty screens (i.e., screens displaying only the road or

Fig. 2: Truck driver participant and data collector in the experiment room

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Fig. 3: Screen of urban daytime and urban nighttime scenarios

other vehicles without motorcycles). In the RD scenario, there were 90 total stimuli, consisting of 45 empty screens and 15 motorcycles appearing in front, 15 on the right, and 15 on the left of the truck. The RN scenario included 87 stimuli (42 empty, 15 front, 15 right, 15 left), the UD scenario included 83 stimuli (41 empty, 12 front, 15 right, 15 left), and the UN scenario included 105 stimuli (52 empty, 23 front, 15 right, 15 left). The number of motorcycles was allocated to maintain opportunities for detection across screen positions (front, left, right) while including empty screens to simulate realistic driving conditions and avoid expectancy effects. The slight variations in total stimuli were intentional to balance visual complexity, expectancy, and realism—for example, urban daytime had fewer motorcycles in front due to higher visual clutter, whereas urban nighttime included more to ensure sufficient detection events under low visibility conditions.

To account for potential circadian effects on cognitive performance, participants were tested at different times of the day. Given the importance of aligning testing times with participants' optimal alertness periods, the study incorporated two testing sessions per day. Session 1 took place from 08:00 to 10:30 AM, and Session 2 from 11:00 AM to 01:30 PM. These time windows were selected based on previous research showing that cognitive performance remains stable during these periods and is less influenced by circadian dips in alertness[57–59].

To ensure participants were not distracted by hunger or fullness, participants in Session 1 were tested after breakfast. In Session 2, participants were provided with a light snack at 10:00 AM to avoid hunger without causing excessive fullness, which could impair focus. Furthermore, participants were prohibited from smoking[60] and consuming caffeine[61] while iddle time to control for potential influences on Heart Rate Variability.

3. Data Collection and Analysis

3.1. Data Collection

The data collection process in this study involved gathering NASA-TLX responses, HRV measurements, and driving performance metrics from participants while they performed simulated motorcycle detection tasks across four driving scenarios. Before the experiment, participants complete a demographic questionnaire to establish baseline characteristics. A heart rate monitor sensor is attached to the participant named by Polar H10 to record their heart beat data. Polar H10 is paired with the Elite HRV software to get beat-to-beat heart rate data (IBI), which is converted into RR interval data in .txt file extension. Key HRV metrics such are absolute Low Frequency (aLF) power, absolute High Frequency (aHF) power, ln-aLF, ln-aHF, normalised Low Frequency (nLF) power, normalised High Frequency (nHF) power, and Heart Rate (HR) in bpm. The mean scores are extracted with Kubios HRV for further analysis. Kubios HRV Scientific analysis software, considered the gold standard for Heart Rate Variability research, was utilized in this study (Ashok et al., 2022).

Driving performance was measured in terms of response time, hit rate, and error rate. Hit rate was defined as the ratio of hits (participant correctly detected a motorcycle when it appeared) to the sum of hits and misses (participant failed to detect a motorcycle when it appeared). Error rate was calculated as the ratio of errors (participant indicated a motorcycle when none appeared, i.e., false alarms) to the total number of stimuli.

3.2. Data Analysis Method

In this study, one-way Repeated Measures (RM) ANOVA was used to examine significant differences ($p < 0.05$) in mental workload and driving performance across the four specific driving scenarios. A pairwise comparison with Bonferroni correction was conducted to determine significant differences ($p < 0.05$) between the two driving scenarios. A paired-sample *t*-test was also conducted to compare HRV indicators between the resting condition and the aggregated driving scenarios. In addition, two-way RM ANOVA was conducted with road condition (rural vs. urban) and driving time (daytime vs. nighttime) as factors, enabling the assessment of the main effects of each factor as well as their interaction, thereby providing a clearer understanding of how environmental and temporal factors jointly influence both subjective and objective measures of mental workload.

The assumption of sphericity was tested using Mauchly's Test. If the assumption was violated ($p < 0.05$), Greenhouse-Geisser correction was applied for the degrees of freedom, and Huynh-Feldt correction was used when Greenhouse-Geisser epsilon (ε) exceeded 0.75.

3.3. Ethical Considerations

This study has received ethics committee approval from The Ethics Committee on Social Studies and Humanities National Research and Innovation Agency (NRIA) with approval number 026/KE.01/SK/01/2024, ensuring that all participants are granted the right to withdraw at any time without consequences. Participant data is kept confidential and is used solely for research purposes.

4. Results

4.1. One-way RM ANOVA

The descriptive statistics and significance markers of the one-way RM ANOVA results for NASA-TLX measurements across different driving scenarios are presented in Table 1, and the results of the pairwise comparisons are visualized in Figure 4. Overall, no statistically significant differences among the driving scenarios were observed in the mean scores of total mental workload, $F(3,147) = 1.131$, $p\ (0.338) > 0.05$, $\eta_p^2 = 0.023$, MSE= 114.299, as the assumption of sphericity was met, $p\ (0.443) > 0.05$. However, all participants subjectively agreed that total mental workload increased progressively as driving scenario transitioned from rural daytime to urban nighttime, where traffic density was higher and visibility was lower. The total mental workload exhibited an increasing pattern, with higher mean scores observed in rural daytime (41.58 ± 2.61), rural nighttime (44.05 ± 2.72), urban daytime (44.28 ± 2.37), and urban nighttime (45.39 ± 2.49), respectively (see Table 1).

The other results (see Table 1) showed that Mental Demand peaked in urban nighttime (36.90 ± 3.75), slightly above rural nighttime and urban daytime. Frustration followed a similar pattern, highest in urban nighttime (30.45 ± 3.45) and lowest in rural daytime (23.50 ± 3.10), with rural nighttime and urban daytime remaining comparable. Temporal Demand rose sharply in urban nighttime (33.50 ± 3.50) relative to rural daytime (26.10 ± 3.24). Physical Demand exhibited a fluctuating pattern but appeared tiered according to environmental factors, with rural daytime (31.30 ± 3.86) > rural nighttime (30.40 ± 3.28) and urban nighttime (35.60 ± 3.53) > urban daytime (29.60 ± 3.43). Performance ratings dropped gradually in urban nighttime (65.70 ± 3.78) compared to other scenarios respectively, highlighting a potential impact of higher workload and stress on task effectiveness.

Table 1: Descriptive statistics and significance markers for ASA-TLX measurements

Mental Workload Dimension	Mean (Standard Error of the Mean)			
	RD	RN	UD	UN
Total Mental Workload	41.58 (2.61)	44.05 (2.72)	44.28 (2.37)	45.39 (2.49)
Mental Demand (MD)[a]	27.60 (3.84)	33.36 (3.85)	33.78 (3.66)	36.90 (3.75)
Physical Demand (PD)	31.30 (3.86)	30.40 (3.28)	29.60 (3.43)	35.60 (3.53)
Temporal Demand (TD)[a]	26.10 (3.24)	28.16 (3.35)	32.14 (3.48)	33.50 (3.50)
Frustation (FR)	23.50 (3.10)	27.24 (3.49)	26.84 (2.95)	30.30 (3.45)
Effort (EF)	43.80 (4.06)	50.00 (4.56)	46.32 (4.34)	49.30 (4.31)
Performance (PF)	73.50 (4.08)	72.04 (3.39)	73.36 (3.32)	65.70 (3.78)

[a] *means statistically significant at $p < 0.05$.*

For Mental Demand, the assumption of sphericity was met, $p\ (0.762) > 0.05$, and the main effect of driving scenario was statistically significant, $F(3,147) = 2.855$, $p\ (0.039) < 0.05$, $\eta_p^2 = 0.055$, MSE= 263.097. Similarly, for Temporal Demand, the assumption of sphericity was also met, $p\ (0.07) > 0.05$, and a significant main effect of driving scenario was observed, $F(3,147) = 3.118$, $p\ (0.028) < 0.05$, $\eta_p^2 = 0.06$, MSE = 189.324. During the task of observing and reporting the appearance of motorcyclists, the partial eta squared values revealed that 5.5% and 6% of the significant differences between driving scenarios could be explained by the Mental Demand and Temporal Demand factors, respectively. Notably, regarding to pairwise comparisons shown in Figure 4, Mental Demand was significantly higher in urban nighttime compared to rural daytime, $p\ (0.025) < 0.05$. Similarly, Temporal Demand also showed significant differences between these scenarios, $p\ (0.047) < 0.05$.

Conversely, no significant differences in Physical Demand were found between the driving scenarios, $F(3,147) = 1.458$, $p\ (0.229) > 0.05$, $\eta_p^2 = 0.029$, MSE= 245.462, as the assumption of sphericity was met, $p\ (0.059) > 0.05$. Similarly, for Frustration, the assumption of sphericity was violated, $p\ (0.042) < 0.05$, Greenhouse-Geisser was not met, $\varepsilon\ (0.872) > 0.75$, so Huynh-Feldt correction was applied, $\varepsilon\ (0.925) > 0.75$, resulting also in a non-significant main effect of driving scenario, $F(2.78,136.03) = 1.776$, $p\ (0.154) > 0.05$, $\eta_p^2 = 0.035$, MSE= 235.469. No significant effect of driving scenario were also found for Effort, $F(2.55,124.87) = 1.096$, $p\ (0.348) > 0.05$, $\eta_p^2 = 0.022$, MSE= 438.403 (assumption of sphericity was violated, $p\ (0.002) < 0.05$, Greenhouse-Geisser was not met, $\varepsilon\ (0.805) > 0.75$, and Huynh-Feldt correction was applied, $\varepsilon\ (0.849) > 0.75$), and Performance, $F(2.68,131.38) = 1.792$, $p\ (0.158) > 0.05$, $\eta_p^2 = 0.035$, MSE= 425.635 (assumption of sphericity was violated, $p\ (0.035) < 0.05$, Greenhouse-Geisser was not met, $\varepsilon\ (0.844) > 0.75$, and Huynh-Feldt correction was applied, $\varepsilon\ (0.894) > 0.75$).

Table 2 presents the descriptive statistics and significance markers of the one-way RM ANOVA results for HRV measurements across different driving scenarios. The analysis revealed a significant main effect of driving scenarios only happened on nLF power, $F(3,147) = 2.824$, $p\ (0.04) < 0.05$, $\eta_p^2 = 0.055$, MSE= 55.891, where assumption of sphericity was met, $p\ (0.97) > 0.05$, and Heart Rate, $F(3,147) = 5.396$, $p\ (0.001) < 0.05$, $\eta_p^2 = 0.099$, MSE= 6.791, assumption of sphericity was met, $p\ (0.28) >$

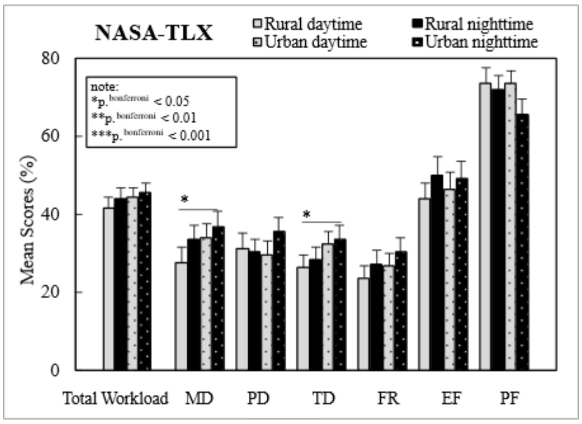

Fig. 4: Pairwise comparisons of NASA-TLX dimensions

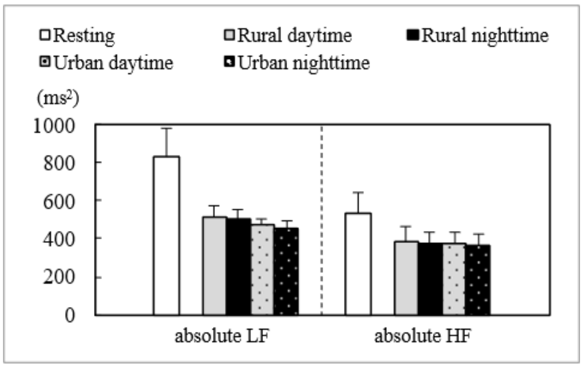

Fig. 5: Pairwise comparisons of aLF and aHF power across driving scenarios

0.05, indicating that autonomic nervous system activity and physiological arousal levels varied significantly depending on the detecting motorcycle environment.

Figure 5 illustrates the aLF and aHF power of HRV across different driving scenarios, including resting. The main effect of driving scenario was not statistically significant for the aLF power, as the assumption of sphericity was violated, p (0.003) < 0.05, Greenhouse-Geisser was not met, ε (0.807) > 0.75, so Huynh-Feldt correction was applied, ε (0.852) > 0.75, $F(2.56,125.27)= 1.631$, p (0.192) > 0.05, $\eta_p^2 = 0.032$, MSE= 33206.528. The results also reveal no significant main effect of driving scenario on an aHF power of HRV, $F(2.23,109.07)= 0.2$, p (0.841) > 0.05, $\eta_p^2 = 0.004$, MSE= 24200.521, assumption of sphericity was violated, p (0.000) < 0.05, but Greenhouse-Geisser was met, ε (0.742) < 0.75.

Additionally, mean aLF values indicated a significant difference between the resting state and driving scenarios, $t(49) = 2.902$, p (0.006) < 0.05, with aLF during rest (837.84 ± 143.26) substantially higher than during driving scenarios (486.48 ± 43.86), representing a decrease of approximately 41.96%. This suggests a marked reduction in autonomic activity associated with the transition from rest to active driving conditions. In contrast, aHF showed no statistically significant difference between resting and driving scenarios, $t(49) = 2.750$, p (0.734) > 0.05, with mean values of 538.84 ± 108.96 during rest and 376.74 ± 63.41 during driving scenarios. Although not significant, the descriptive statistics indicated a downward trend in aHF during driving, suggesting a possible reduction in parasympathetic modulation that did not reach statistical significance.

Table 2: Descriptive statistics and significance markers for HRV measurements

HRV indicators	Mean (Standard Error of the Mean)				
	Resting	RD	RN	UD	UN
aLF	837.84 (143.26)	517.76 (56)	504.54 (54.29)	470.60 (36.16)	451.66 (44.78)
aHF	538.84 (108.96)	387.34 (78.55)	377.04 (58.20)	374.24 (63.62)	366.88 (59.64)
ln-aLF	6.22 (1.05)	5.97 (0.82)	5.92 (0.87)	5.95 (0.79)	5.83 (0.87)
ln-aHF	5.56 (1.27)	5.14 (1.38)	5.25 (1.38)	5.23 (1.35)	5.24 (1.32)
nLF[a]	65.00 (2.15)	66.74 (2.71)	64.01 (2.24)	64.26 (2.62)	62.44 (2.48)
nHF	37.24 (2.57)	36.65 (2.92)	36.56 (2.33)	36.53 (2.66)	36.28 (2.70)
HR[b]	78.98 (1.68)	79.36 (1.67)	79.66 (1.76)	77.90 (1.72)	78.22 (1.66)

[a] means statistically significant at $p < 0.05$ and [b] means statistically significant at $p < 0.01$.

Figure 6 presents the Bonferroni-adjusted comparisons, showing that nLF power during rural daytime driving was significantly different from urban nighttime, p (0.028) < 0.05, indicating higher sympathetic modulation in the rural daytime condition compared to the urban nighttime scenario. In contrast, nHF showed no significant differences across all driving scenarios, $F(2.52,123.48)= 0.01$, p (0.99) > 0.05, $\eta_p^2 = 0.000$, MSE= 142.24, where assumption of sphericity was violated, p (0.005) < 0.05, Greenhouse-Geisser was not met, ε (0.796) > 0.75, and Huynh-Feldt correction was applied, ε (0.84) > 0.75. Descriptively, nHF exhibited a slight downward trend from rural daytime to rural nighttime, urban daytime, and urban nighttime, but this change was minimal compared to the more pronounced decrease observed in nLF. This suggests that while sympathetic activity varied considerably across scenarios, parasympathetic activity remained relatively stable.

Regarding the comparison between resting and driving scenarios, nLF power did not differ significantly, $t(49) = 0.339$, p (0.736) > 0.05. Similarly, nHF power showed no significant difference, $t(49) = 0.301$, p (0.765) > 0.05.

Figure 7 illustrates the pairwise comparisons of heart rate (HR, bpm) across driving scenarios. The analysis revealed a significant main effect, $F(3, 147) = 5.396$, $p = 0.001 < 0.05$, $\eta_p^2 = 0.099$, MSE = 6.791, with the assumption of sphericity met ($p = 0.284 > 0.05$). Bonferroni-adjusted post hoc tests indicated that HR was higher during rural nighttime (79.66 ± 1.76) compared to urban daytime

(77.90 ± 1.72), p = 0.023 < 0.05, and slightly significance (p = 0.05) when compared to urban nighttime (78.22 ± 1.66).

When comparing the resting period with the aggregated driving scenarios, no significant difference was found, t(49) = 0.342, p = 0.734 > 0.05. However, the descriptive statistics showed a slight increase in HR from the resting state to periods with task demand, suggesting a modest physiological adjustment to driving engagement that was not statistically significant.

Table 3 presents the descriptive statistics and one-way RM ANOVA results for key performance indicators in truck driving across different scenarios. The result reveals statistically significant differences (p < 0.001) across all measured variables. Response time varied notably across conditions, with the slowest responses recorded during rural nighttime (1779.07 ms ± 55.47), suggesting increased

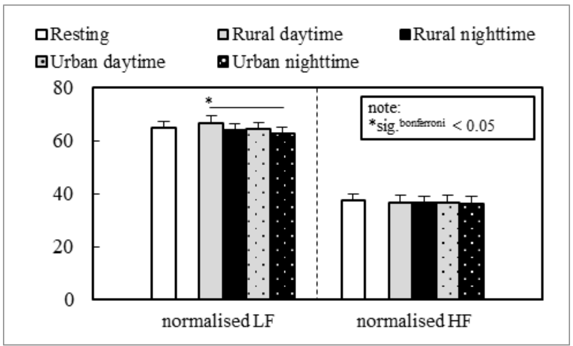

Fig. 6: Pairwise comparisons of nLF and nHF power across driving scenarios

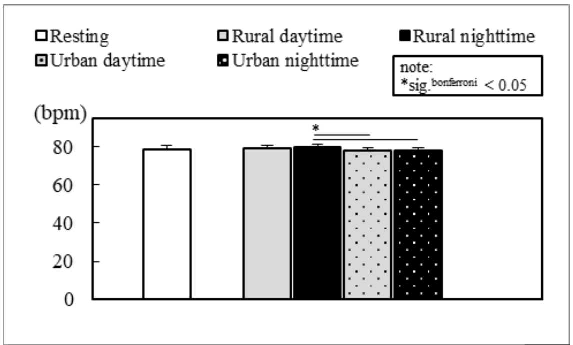

Fig. 7: Pairwise comparisons of HR in bpm across driving scenarios

Table 3: Descriptive statistics and significance markers for performance measurements

Performance Indicators	Mean (Standard Error of the Mean)			
	RD	RN	UD	UN
Response time (ms)[a]	1409.40 (32.48)	1779.07 (55.47)	1604.98 (31.06)	1423.10 (38.37)
Hit rate (%)[a]	86.67 (2.49)	91.11 (2.34)	72.62 (2.09)	77.36 (1.94)
Error rate(%)[a]	0.53 (0.94)	0.80 (1.46)	1.30 (1.97)	1.92 (2.57)

[a] *means statistically significant at p < 0.001.*

cognitive demand and reduced alertness. In contrast, urban nighttime resulted in the fastest response times (1423.10 ms ± 38.37), potentially attributable to the headlamp's spectral characteristics producing greater luminance contrast against the low-light background. This enhanced contrast likely facilitated more efficient photoreceptor activation and subsequent visual signal transduction, thereby accelerating the initiation of motor responses. Urban daytime (1604.98 ms ± 31.06) and rural daytime (1409.40 ms ± 32.48) of driving scenarios exhibited intermediate response times, implying that urban settings impose greater situational demands during the day, while rural nighttime conditions exacerbate cognitive strain.

Hit rate also demonstrated significant variation, with the highest accuracy observed during rural nighttime (91.11% ± 2.34%), potentially indicating compensatory cognitive mechanisms in low-visibility conditions. Conversely, urban daytime resulted in the lowest hit rate (72.62% ± 2.09%), reflecting the complex and dynamic nature of urban traffic environments. Rural daytime (86.67% ± 2.49%) and urban nighttime (77.36% ± 1.94%) conditions fell in between, further suggesting that lighting and environmental context play a crucial role in performance accuracy.

Error rate followed a distinct pattern, with the highest error rate recorded under urban nighttime conditions (1.92 ± 2.57), suggesting increased cognitive strain and task difficulty in low-light urban environments. Urban daytime (1.3 ± 1.97) also exhibited a high error rate, reinforcing the notion that urban settings impose greater attentional demands. In contrast, rural nighttime and rural daytime showed lower error rate.

Figure 8 illustrates the pairwise comparisons of response time across the four driving scenarios. The analysis revealed a highly significant main effect, $F(2.41,117.92)= 35.67$, $p\ (0.000) < 0.001$, $\eta_p^2 = 0.421$, MSE= 53182.97, where assumption of sphericity was violated, p (0.000) < 0.05, Greenhouse-Geisser was not met, ε (0.763) > 0.75, and Huynh-Feldt correction was applied, ε (0.802) > 0.75. Bonferroni-adjusted post hoc comparisons indicated highly significant differences between several scenario pairs (p (0.000) < 0.001). Specifically, response times were longer in rural daytime compared to rural nighttime and urban daytime, and in rural nighttime compared to both urban daytime and urban nighttime. Furthermore, urban daytime produced significantly slower responses than urban nighttime. These patterns demonstrate that environmental context and lighting conditions jointly influence driver reaction speed, with urban nighttime consistently associated with the fastest responses.

Figure 9 depicts the pairwise comparisons of hit rate across the four driving scenarios. The analysis demonstrated a highly significant main effect of driving scenarios on hit rate, $F(2.45,120.09)= 28.23$, $p\ (0.000) < 0.001$, $\eta_p^2 = 0.366$, MSE= 101.85, where assumption of sphericity was

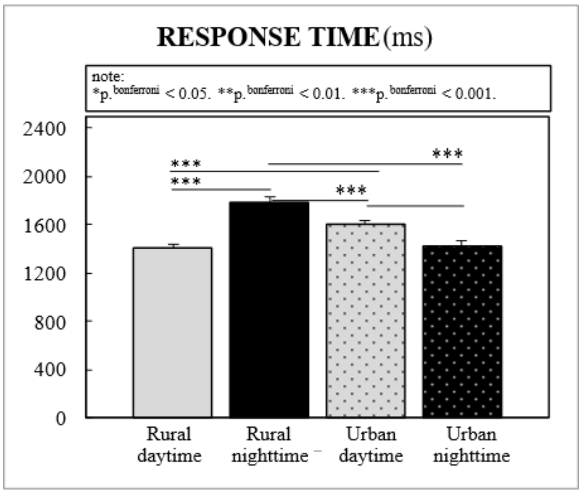

Fig. 8: Pairwise comparisons of response time on different driving scenarios

violated, p (0.001) < 0.05, Greenhouse-Geisser was not met, ε (0.776) > 0.75, and Huynh-Feldt correction was applied, ε (0.817) > 0.75. Bonferroni-adjusted post hoc comparisons revealed highly significant differences ($p < 0.05$ to $p < 0.001$) between several pairs of scenarios. Hit rates were notably higher in rural nighttime compared to rural daytime, urban daytime, and urban nighttime. Additionally, urban nighttime achieved significantly higher hit rates than urban daytime ($p = 0.011 < 0.05$). These findings indicate that detection performance peaked under rural nighttime conditions, with urban nighttime also outperforming urban daytime, suggesting that certain nighttime environments may enhance target detection accuracy.

Figure 10 shows the pairwise comparisons of error rate across the four driving scenarios. The analysis demonstrated a highly significant main effect of driving scenarios on error rate, F(2.48,121.54)= 9.706, p (0.000) < 0.001, η_p^2= 0.165, MSE= 2.328, where assumption of sphericity was violated, p (0.002) < 0.05, Greenhouse-Geisser was not met, ε (0.785) > 0.75, and Huynh-Feldt correction was applied, ε (0.827) > 0.75.

4.2. Two-way RM ANOVA

Further analysis of the two-way RM ANOVA was conducted and the results are presented in Table 4. Regarding subjective mental workload, road condition was statistically significant only for Temporal Demand, where 11% of the variability in Temporal Demand can be attributed to differences between rural and urban road conditions, F(1,49) = 5.89, p (0.02) < 0.05, η_p^2 = 0.11, MSE = 274.825. Temporal Demand was significantly higher in urban conditions (32.82 ± 3.27) compared to rural conditions (27.13 ± 3.05). However, the effect of driving time on Temporal Demand was not significant. Driving time showed a significant effect in Mental Demand and Frustation. The Mental Demand, F(1,49) = 4.975, p (0.03) < 0.05, η_p^2 = 0.09, MSE = 198.129, was significantly higher during nighttime (35.1 ± 3.39) compared to daytime (30.69 ± 3.31), with the effect size suggesting a small to moderate effect (9%). The Frustation dimension, F(1,49) = 4.543, p (0.04) < 0.05, η_p^2 = 0.09, MSE = 142.643, was significantly higher during nighttime (28.8 ± 2.97) compared to daytime (25.17 ± 2.68), with the effect size similar to Mental Demand's. In addition, the interaction between road condition and driving time was not significant for any of the NASA-TLX indicators.

Regarding objective mental workload, road condition was statistically significant for nLF, nHF, and HR, with the effect size for HR being the largest (17%), compared to nLF and nHF, both of which had an effect size of 11%. The nLF power, F(1,49) = 5.74, p (0.02) < 0.05, η_p^2 = 0.11, MSE = 70.819, was significantly lower in urban conditions (64.75 ± 2.29) compared to rural conditions (67.59 ± 2.11). The nHF power, F(1,49) = 5.74, p (0.02) < 0.05, η_p^2 = 0.11, MSE = 70.815, was significantly lower in urban conditions (32.41 ± 2.11) compared to rural conditions (35.26 ± 2.29). Then the HR in bpm, F(1,49) = 9.745, p (0.003) < 0.05, η_p^2 = 0.17, MSE = 9.771, was significantly higher in urban conditions (79.4 ± 1.71) compared to rural conditions (78.02 ± 1.67). However, the effect of driving time was not significant, nor was the interaction between driving time

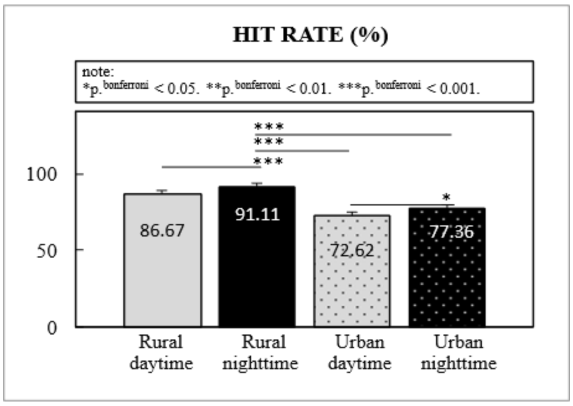

Fig. 9: Pairwise comparisons of hit rate on different driving scenarios

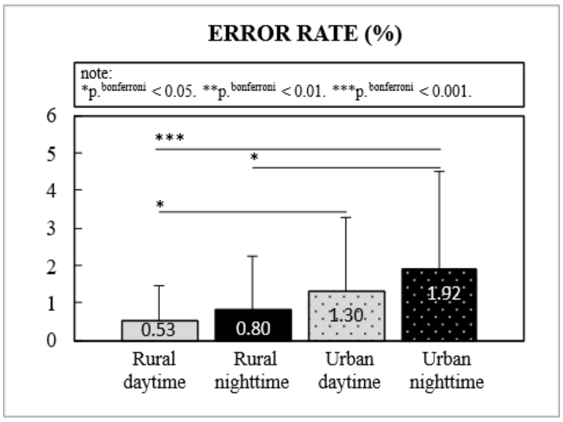

Fig. 10: Pairwise comparisons of error rate on different driving scenarios

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Table 4: Summarized results of two-way RM ANOVA

Measures	Road Condition (RC)	Driving Time (DT)	RC*DT
	p (η_p^2)	p (η_p^2)	p (η_p^2)
NASA-TLX			
Total Mental Workload	N.S.	N.S.	N.S.
Mental Demand	N.S.	0.03 (0.09)	N.S.
Physical Demand	N.S.	N.S.	N.S.
Temporal Demand	0.02 (0.11)	N.S.	N.S.
Frustation	N.S.	0.04 (0.09)	N.S.
Effort	N.S.	N.S.	N.S.
Performance	N.S.	N.S.	N.S.
HRV			
aLF	N.S.	N.S.	N.S.
aHF	N.S.	N.S.	N.S.
nLF	0.02 (0.11)	N.S.	N.S.
nHF	0.02 (0.11)	N.S.	N.S.
HR	0.003 (0.17)	N.S.	N.S.
Driving performance			
Response time	0.02 (0.11)	0.001 (0.22)	[a] (0.64)
Hit rate	[a] (0.5)	[a] (0.33)	N.S.
Error rate	[a] (0.24)	0.01 (0.12)	N.S.

[a] means statistically significant at p < 0.001 and N.S. denotes not statistically significant.

and road condition for any of the HRV indicators.

Regarding driving performance, the effect of road condition was significant for all indicators. The effect size of road condition was 50%, 24%, and 11% for hit rate, error rate, and response time, respectively. The response time, $F(1,49) = 6.267$, $p\ (0.016) < 0.05$, $\eta_p^2 = 0.113$, MSE = 51312.862, was significantly faster in urban (1514.037 ± 30.36) compared to rural (1594.24 ± 39.95). The hit rate, $F(1,49) = 48.368$, $p < 0.001$, $\eta_p^2 = 0.497$, MSE = 116.498, was significantly better in rural (82.76 ± 2.30) compared to urban (72.14 ± 1.81). The error rate, $F(1,49) = 15.34$, $p < 0.001$, $\eta_p^2 = 0.24$, MSE = 2.902, was significantly lower in rural (0.67 ± 0.13) compared to urban (1.61 ± 0.29). Hence, driving time also showed a significant effect, with effect sizes for hit rate, response time, and error rate being 33%, 22%, and 12%, respectively. The response time, $F(1,49) = 13.62$, $p\ (0.001) < 0.01$, $\eta_p^2 < 0.217$, MSE = 32375.204, was significantly faster in daytime (1507.19 ± 28.14) compared to nighttime (1601.09 ± 39.20). The hit rate, $F(1,49) = 24.05$, $p < 0.001$, $\eta_p^2 = 0.329$, MSE = 58.02, was significantly better in nighttime (80.09 ± 1.87) compared to daytime (74.81 ± 2.12). The error rate, $F(1,49) = 6.45$, $p\ (0.01) < 0.05$, $\eta_p^2 = 0.12$, MSE = 1.548, was significantly lower in daytime (0.92 ± 0.18) compared to nighttime (1.36 ± 0.24). A significant road condition x driving time interaction was found for response time ($F(1,49) = 85.85$, $p < 0.001$, $\eta_p^2 = 0.22$, MSE = 44297.19).

5. Discussion

The present study provides empirical evidence that both environmental context (rural vs. urban) and temporal factors (daytime vs. nighttime) significantly modulate mental workload and performance in professional truck drivers. Importantly, the two-way RM ANOVA results highlight that driving time primarily affects mental demand and frustration, whereas road condition predominantly influences temporal demand and physiological indices such as HR and HRV parameters (nLF, nHF). These findings underscore the multidimensional nature of workload, where temporal and spatial elements interact with drivers' cognitive resources in distinct ways.

Consistent with previous research, nighttime driving elevated subjective mental demand and frustration compared to daytime conditions, reflecting the influence of reduced visibility and circadian rhythm disruptions on attentional control and affective states[37,45)]. Elevated mental demand at night also aligns with studies reporting slower information processing and higher error proneness under dark conditions[44,46)]. Interestingly, although daytime driving produced faster response times, nighttime conditions yielded higher hit rates, suggesting compensatory attentional mechanisms may be recruited to counteract low-visibility challenges[42)].

Road condition effects were equally salient. Urban driving elicited significantly higher temporal demand, error rate, and heart rate compared to rural driving. These results reflect the increased environmental complexity in urban contexts, where dense traffic, frequent stops, and visual clutter heighten cognitive load and sympathetic activation[38,39)]. The reduction in HRV indices (nLF and nHF) under urban conditions suggests diminished autonomic flexibility, an established marker of stress and reduced capacity for adaptive responses[34,48)]. By contrast, rural driving—although monotonous—was associated with better performance outcomes (higher hit rate, lower error rate), consistent with earlier findings that monotony induces underload rather than overload, thereby posing risks for fatigue-induced lapses rather than acute cognitive overload[40,41)].

A particularly noteworthy finding is the interaction effect between road condition and driving time on response time. Urban nighttime driving produced the fastest responses, which may be explained by enhanced luminance contrast from vehicle headlamps and urban lighting infrastructure, facilitating quicker visual signal transduction and motor initiation. This resonates with previous simulator studies showing that spectral qualities of artificial lighting can improve target detectability in low-light environments[45]. However, the faster responses did not translate into improved accuracy, as error rates remained highest under the same condition. This dissociation suggests that while perceptual speed may improve, cognitive control and decision accuracy are compromised, emphasizing the dual-edged nature of urban nighttime driving for truck drivers.

From an applied perspective, these results highlight the need for workload management strategies tailored to both temporal and spatial driving contexts. Nighttime operations require interventions to mitigate elevated mental demand and frustration, such as adaptive lighting systems, scheduling strategies to align with circadian rhythms, and real-time workload monitoring using physiological sensors. Conversely, urban driving demands solutions that address environmental overload, including driver-assist technologies (e.g., collision warning, adaptive cruise control) and road infrastructure improvements to reduce cognitive fragmentation[25,28].

Limitation of this study is the use of a video-based methodology, which, while useful for controlled testing, does not fully replicate real-world driving conditions. The video format lacks the dynamic and immersive experience of actual driving, where factors such as weather conditions, traffic density, and environmental stimuli significantly influence driver performance and mental workload. Furthermore, this study did not account for other factors that could affect driving performance, such as weather conditions, which may increase cognitive demands and affect reaction times, and traffic density, which could elevate mental workload due to the need for frequent decision-making and hazard anticipation. Additionally, driver-specific factors, such as fatigue, chronotype, and experience, were not controlled, and may have influenced the results. These limitations suggest that future studies should incorporate real-world driving simulations and account for these external factors to improve the ecological validity of the findings.

6. Conclusion

This study examined the effects of driving scenarios and effects of road condition (rural vs. urban) and driving time (day vs. night) factors on mental workload in professional truck drivers. Using both subjective (NASA-TLX) and objective (HRV) workload measures, as well as performance metrics (response time, hit rate, and error rate), the findings provide valuable insights into the cognitive demands of detecting motorcycles under varying conditions.

The results indicate that mental workload, as measured by NASA-TLX, increases progressively from rural daytime to urban nighttime detecting motorcycles. Although total workload did not show statistically significant differences, Mental Demand, and Temporal Demand were significantly higher in urban nighttime conditions, reflecting increased cognitive strain due to reduced visibility and higher traffic complexity. These findings suggest that urban nighttime imposes greater perceptual and decision-making burdens on drivers, leading to elevated mental effort.

Objective physiological measures further support these observations. Heart rate variability (HRV) analysis revealed that normalized low-frequency power (nLF) was significantly lower in urban nighttime, indicating a shift toward increased cognitive workload and stress. Heart rate (HR) was also considerably elevated during the detection of motorcycles compared to resting conditions, particularly in rural daytime scenarios, suggesting heightened physiological arousal. However, absolute HRV components (aLF and aHF) remained relatively stable, indicating that overall autonomic balance was maintained despite varying conditions.

Performance measures further highlight the impact of environmental and temporal factors on driver workload. Response times were slowest in rural nighttime conditions, likely due to reduced external stimuli and lower alertness. However, error rate were highest in urban nighttime conditions, reinforcing the idea that complex traffic environments, especially at night, place greater cognitive demands on drivers. Hit rates were significantly lower in urban conditions, particularly during the daytime, suggesting that increased situational complexity reduces detection accuracy.

Taken together, these findings demonstrate that urban nighttime imposes the highest cognitive and physiological workload, leading to increased response times, reduced accuracy, and a higher errors. The combination of traffic density, reduced visibility, and heightened attentional demands contributes to increased driver strain. In contrast, rural daytime imposes the least cognitive workload, with lower heart rates, faster response times, and fewer errors.

These insights have important implications for road safety and fatigue management strategies. Given the increased cognitive demands of nighttime urban, adaptive workload management strategies, improved roadway lighting, and driver assistance systems should be prioritized to enhance performance and reduce errors. Furthermore, incorporating real-time HRV-based monitoring into fatigue detection systems could help mitigate cognitive overload and enhance overall driving safety. Future research should explore interventions that optimize driver workload and resilience, particularly under challenging driving scenarios.

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