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Fatigue analysis and design of a motorcycle online driver measurement tool using real-time sensors

Iwan Aang Soenandi[1*], Lamto Widodo[2], Budi Harsono[3], Isnia Oktavera[2], Vera Lusiana[1]

[1] Department of Industrial Engineering, Universitas Kristen Krida Wacana, Jl. Tanjung Duren Raya no. 4, Jakarta, 11470, Indonesia
[2] Department of Industrial Engineering, Universitas Tarumanagara, Jl. Letjen S. Parman No.1, Jakarta 11440, Indonesia
[3] Department of Electrical Engineering, Universitas Kristen Krida Wacana, Jl. Tanjung Duren Raya no. 4, Jakarta, 11470, Indonesia

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*Corresponding Author

Iwan Aang Soenandi
E-mail: iwan.as@ukrida.ac.id

A B S T R A C T

Work fatigue is an important aspect and is very influential in determining the level of accidents, especially motorbike accidents. According to WHO, almost 30% of all deaths due to road accidents involve two- and three-wheeled motorized vehicles, such as motorbikes, mopeds, scooters and electric bicycles (e-bikes), and the number continues to increase. Motorcycles dominate road deaths in many low- and middle-income countries, where nine out of ten traffic accident deaths occur among motorcyclists, as in Indonesia. However, until now, in Indonesia, there has been no monitoring system capable of identifying fatigue in motorbike drivers in the transportation sector. This research aims to determine fatigue patterns based on driver working hours and create a sensor system to monitor fatigue measurements in real-time to reduce the number of accidents. The research began with processing questionnaire data with Pearson correlation, which showed a close relationship between driver fatigue and driving time and a close relationship between fatigue and increased heart rate and sweating levels. From calibration tests with an error of 3% and direct measurements of working conditions, it was found that two-wheeled vehicle driver fatigue occurs after 2-3 hours of work. With a measurement system using the Box Whiskers analysis method, respondents' working conditions can also be determined, which are divided into 4 zones, namely zone 1 (initial condition or good condition), zone 2 a declining condition, zone 3 a tired condition and zone 4 is a resting condition. Hopefully, this research will identify fatigue zones correctly and reduce the number of accidents because it can identify tired drivers so they do not have to force themselves to continue working and driving their motorbikes. As a conclusion from this research, a measurement system using two sensors, such as ECG and GSR can identify work fatigue zones well and is expected to reduce the number of accidents due to work fatigue.

1. INTRODUCTION

Mobility from one place to another is necessary for the community, especially in densely populated urban areas. Safety is a factor that should not be overlooked when working in the increasingly competitive transportation industry. Based on information from WHO, nearly 30% of all road crash deaths involve powered two and three wheeled vehicles, such as motorcycles, mopeds, scooters, and electrical bikes (e-bikes) [1]. Then, based on data from the National Police Traffic Corps, the number of traffic accidents involving motorbikes throughout 2020 reached 93,319 cases. In 2021, it rose to 97,095 cases; in January-August 2022, it reached 85,691 cases. The death toll in 2020 reached 21,525 people, then in 2021, it reached 22,626 people, and in 2022 it reached 16,115 people. It shows that motorbikes dominate the number of accident cases in Indonesia at 81 percent [2]. In the case of an online driver, the ability to work in the transportation field can affect a person's income level. However, this situation should be avoided, especially for motorcycle drivers with a high risk of accidents, especially in Jakarta, if they perform their duties while excessively fatigued [3]. Fatigue is closely related to a person's response to something, especially for tasks like driving, which require concentration and rapid coordination of body parts to drive safely [4]. The speed at which a person responds to an obstacle varies from one individual to another. It is influenced by several factors, such as age, gender, physical endurance, stress, diet, and fatigue [5]. This research will focus only on factors and work-related fatigue, as the diet of two-wheeler riders varies greatly. Fatigue can reduce work capacity and endurance, characterized by feelings of tiredness, decreased motivation, and reduced activity [6]. Fatigue slows reaction time, reduces activity, and makes decision-making difficult, increasing the likelihood of accidents, especially for general vehicle drivers and two-wheeler drivers. Therefore, research on fatigue measurement, especially for two-wheeler drivers, is crucial to reduce the accident rate. Some technologies are believed to be able to be applied to identify this fatigue using sensors [7].

From the literature study, three indicators can be used to detect driver fatigue: driver behavior, vehicle operation, and physiological indexes. Driver behavior-based methods use cameras to monitor the driver's head, eye, facial expressions and body movements to determine driver fatigue. Some important parameters of this method are eye closure, blink duration and frequency, and driver head and body movements. Vehicle operation-based methods use parameters such as driver reaction time, lane position deviation and steering wheel control to predict driver fatigue. Meanwhile, physiological indexes-based methods use several sensors, such as electrocardiogram (ECG), electroencephalogram (EEG), and electrooculography (EOG), to measure body parameters, which are used to determine driver fatigue [8].

Driver behavior-based methods are sensitive to the stability of the camera position and require stable lighting to obtain optimal images for analysis [8]. This method is also unsuitable for two-wheeled vehicles because the driver must wear a helmet to protect their head, so the camera cannot be used to capture the driver's facial expressions. Vehicle operation-based methods depend highly on the driver's skill, condition, and the road travelled. This method can also provide a delayed response because it monitors vehicle movement, not the driver's condition directly. The physiological indexes-based method is a method that can be applied to two-wheeled vehicle drivers. This method accurately and reliably distinguishes awake and asleep states while driving. This method also detects the early stages of drowsiness to provide a faster response than the driver behavior-based method.

Types of physiological sensors that can be used for fatigue measurement include Heart Rate Variability (HRV) [9], Galvanic Skin Response (GSR) [10], ECG [11], and EEG [12]. The characteristics of these sensors will be tested in combination to identify fatigue measurement accurately, for example, by measuring HRV with sweat sensors (Galvanic Skin Response). This research did not use EEG sensors because they are expensive and highly susceptible to distortion from motor vibrations. Here is the formulation of the research question in this study

RQ1: When does fatigue occur when riding a motorbike in real conditions?

RQ2: How do we measure fatigue using sensors in real-time?

RQ3: How do we validate the signal from the sensor with working conditions by using the sensor until the driver is tired and after resting?

This research provides a sensor system to identify the timing and symptoms of fatigue in online motorcycle drivers based on questionnaire data, and this measurement will be tested using a prototype sensor system to monitor fatigue

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measurement in real time. In general, the research aims to identify the timing and symptoms of fatigue in online motorcycle drivers through questionnaire data, and this measurement will be tested using a prototype sensor system to monitor fatigue measurement in real time.

2. RESEARCH METHODS

This study uses an explanatory research type. The research process, in general, can be seen in Fig. 1. It starts with a literature review to determine the appropriate fatigue measurement method and sensor. This article began with a literature review aimed at collecting information related to determining real-time fatigue signals and the sensors that can be used. The findings of this literature review stated that Heart rate variability (HRV) is the fluctuation in the R-R interval values in an electrocardiogram (ECG) or electroencephalogram (EEG). HRV is one of the parameters widely used to detect fatigue and drowsiness in drivers [13]–[15]. HRV can be measured using various types of sensors, including conventional ECG sensors that use gel electrodes [11], [16]–[20], chest-worn ECG sensors with straps [7], [21], and wrist-worn photoplethysmography (PPG) sensors [22], [23]. Measuring HRV using wrist-worn PPG sensors is the most user-friendly method for drivers, but it is more sensitive to disturbances caused by hand movements compared to HRV measurement using ECG sensors [23], so in this research, we do not use PPG sensors, but one ECG module that used for HRV measurement is the AD8232 module [14].

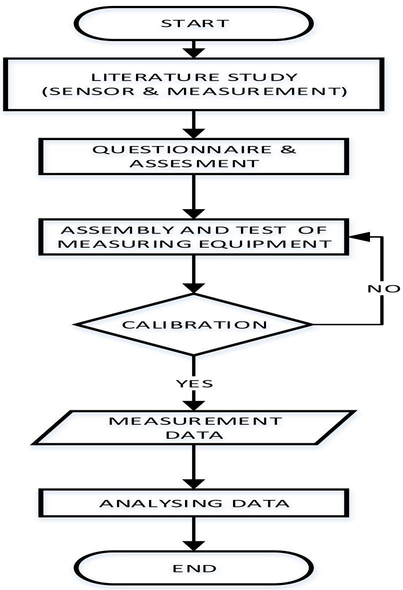
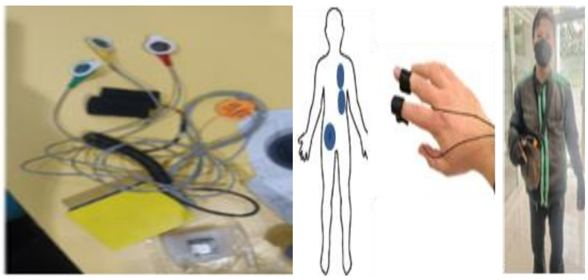


Fig. 1. Research method

This step is followed by a questionnaire randomly distributed to online motorcycle drivers as respondents, and then this questionnaire is analyzed to identify the fatigue condition that occurs in online drivers. This study will compare the results of subjective fatigue measurements (questionnaires) with objective fatigue measurements based on physical or sensor data. Afterwards, the measuring instrument is assembled and calibrated, and data is collected at various measurement intervals such as 1, 2, 3, and 4 hours of driving in real work conditions. Then, the next step is to collect the measurement data from our sensors to identify the fatigue condition of the motorcycle driver.

For the questionnaire phase, thirty healthy participants (25 males and 5 females) completed the entire questionnaire. Demographic characteristics: Age = 26 ± 9 years (mean ± standard deviation), height = 152 ± 9 cm, weight = 55 ± 8 kg. The respondents were in good health and were considered not to require medical permission for health examinations; they only provided informed consent for the research. The questionnaire focuses on individuals' perceptions of fatigue resulting from activities during work/driving. For the questionnaire data processing, descriptive analysis will be conducted [24], and chi-square tests [25] and Pearson correlation tests [26] will be performed. The results of these tests will serve as the basis for the timing of measurements using sensors and objects under conditions of fatigue during daily work.



2a 2b

Fig. 2a. Sensor module set **2b**. Sensor installation ECG and GSR held position on the body and fingers

For the sensor calibration phase and measurements using the sensor during working conditions, 5 healthy participants were randomly selected (all males) with the following demographic characteristics: Age = 25 ± 3 years (mean ± standard deviation), height = 150 ± 5 cm, weight = 52 ± 9

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kg. All test participants were considered healthy because they did not have cardiovascular, metabolic, or kidney diseases and did not exhibit any signs or symptoms of such diseases, allowing them to engage in typical motorbike activities and meet the measurement time targets.

For measurement steps, in this research, the ECG signal is obtained from an ECG sensor with 3 electrodes placed on the body in positions (Fig. 2). The ECG signal obtained from the sensor still contains low-frequency components, causing the ECG signal to oscillate at a certain DC voltage level (Fig. 3 (a)). This ECG signal is then passed through a High Pass Filter (HPF), which also blocks the low-frequency components in the ECG signal, resulting in a smoother or non-oscillating ECG signal (Fig. 3 (b)). The filtered ECG signal is then analyzed to detect the R-wave peaks.

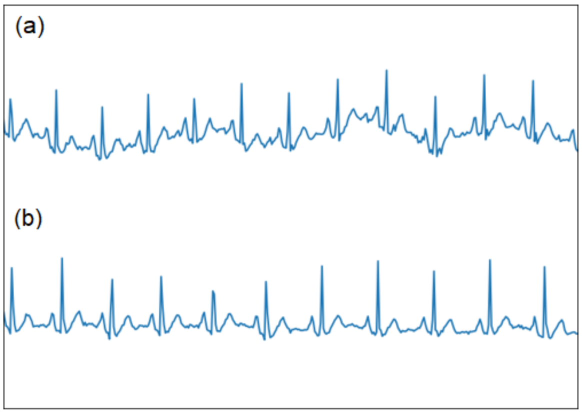

Fig. 3. ECG signal (a) from sensor readings (b) after high pass filter

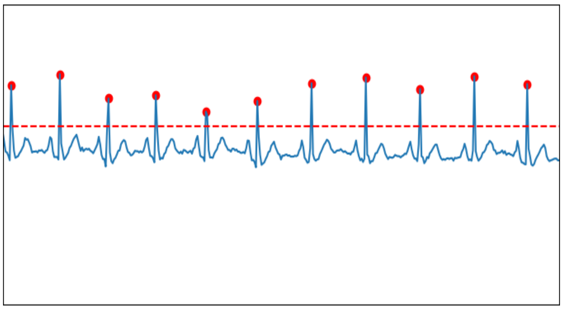

Fig. 4. Results of identifying the R peak in the ECG signal

The first step to detect the R peak is to assign a threshold value to the QRS complex of the ECG signal so that only signals above the threshold value are analyzed [27]. Signal values above the threshold are sorted, and the MAX value is searched to identify the R peak. The time when the R peak occurs is then stored sequentially so that it can be used in calculating the R-R Interval (RR), Heart Rate (HR), and Heart Rate Variability (HRV) values. The results of the R peak identification are given in Fig. 4.

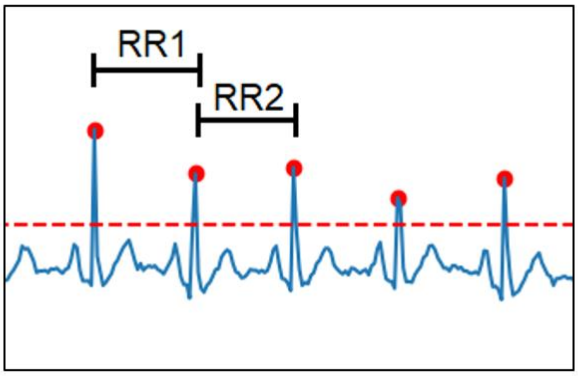

Fig. 5. Illustration of RR calculation

Then, RR (ms) can be obtained by calculating the time interval between two consecutive R-peaks [28], as illustrated in Fig. 5. RR is then calculated using Equation 1, where t_{Rn} is the time of the current R-peak occurrence, and t_{Rn-1} is the time of the previous R-peak occurrence. HR (bpm) can be obtained by estimating the number of R-peaks in one minute. The calculation of HR in this study is performed using Equation 2. HRV (ms) is then calculated using the Root Mean Square of Successive Differences (RMSSD) method [29] using the equation provided in Equation 3.

$$RR = t_{Rn} - t_{Rn-1} \tag{1}$$

$$\mathrm{HR} = \frac{60000}{\mathrm{RR}} \tag{2}$$

$$\mathrm{HRV} = \sqrt{\sum_{i=1}^{n-1}(\mathrm{RR}_{i+1} - \mathrm{RR}_i)^2} \tag{3}$$

Afterwards, we did several calibrations and then utilized measuring instruments to validate the fatigue condition by examining the values obtained from sensor measurement stages of signal processing from sensors (Fig. 6).

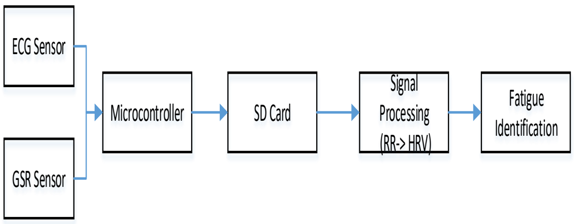

Fig. 6. Stages of signal processing from sensors

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3. RESULTS AND DISCUSSION

In this study, we used questionnaire data as reference data to compare the relationship between driving activities and the occurrence of fatigue. During the questionnaire data collection phase, the focus for obtaining information is on individuals' perceptions of fatigue resulting from activities during work/driving. As shown in Table 1, respondents with less than 1 year of experience are 7 respondents (23.3%), respondents with 1-3 years of experience are 11 respondents (36.6%), and those with more than 3 years of experience are 12 respondents (40%). This condition strengthens the randomness of the data collection process, and the results can be assured to represent an expected population, which means the data sampling from respondents is fulfilled.

Table 1. Frequency distribution of online motorcycle driver employment period

No	Employment period (Year)	Frequency	%
1	<1	7	23.3
2	1-3	11	36.6
3	>3	12	40.0

For time activities of the driver (Table 2), it can be seen that respondents engaged in work activities per day for less than 6 hours are 12 respondents (40%), while respondents working more than 6 hours are 18 (60%). The results of this data collection show that many online motorcycle drivers work long hours, creating the potential for fatigue conditions.

Table 2. Frequency distribution of driver's working hours per day

No	Working (hours)	Frequency	%
1	<6	12	40.0
2	>6	18	60.0

Furthermore, the questionnaire results were analyzed using Chi-Square [25], [30] from McHugh, who proposed the relationships between age and fatigue, gender and fatigue, and working hours and fatigue. As shown in Table 3, the results of the age measurement with fatigue in the 30 online driver respondents who experienced fatigue showed that those aged <30 years were 12 respondents (40%), while respondents aged >30 years with fatigue were 14 respondents (46.6%). Based on the Chi-Square test, a p-value of 0.009 was obtained, indicating a significant relationship between age and respondent's work fatigue.

The questionnaire measurements of gender and fatigue in 30 respondents (Table 4), it can be seen that respondents who experienced fatigue were 23 males (76.6%) and 3 females (10%). The results of the statistical test with Chi-Square were shown to yield a value of 0.753, which means there is no relationship between gender and the occurrence of fatigue. The working hours influence fatigue with a p-value of 0.007, indicating a relationship between working hours and fatigue without considering tedium. Most agree that fatigue occurs after 2-3 hours of non-stop work (Table 5).

Table 3. Frequency distribution of drivers' age and experience of fatigue while working

Ages	Condition						P-Value
	Fatigue		No Fatigue		Total		
	N	%	N	%	N	%	
<30 years	12	40	2	6.67	14	46.67	0.009
>30 years	14	46.66	2	6.67	16	53.33	
Total	26	86.66	4	13.34	30	100	

Table 4. Gender distribution of drivers with fatigue

Gender	Condition						P-Value
	Fatigue		No Fatigue		Total		
	N	%	N	%	N	%	
Male	23	76.66	2	6.67	25	83.33	0.753
Female	3	10.0	2	6.67	5	16.67	
Total	26	86.66	4	13.34	30	100	

Table 5. Frequency distribution of drivers feeling tired

Hours of work	Condition						P-Value
	Fatigue		No Fatigue		Total		
	N	%	N	%	N	%	
2-3	20	66.66	2	6.67	22	73.33	0.007
> 3	6	20.0	2	6.67	8	26.67	
Total	26	86.66	4	13.34	30	100	

In this study, implementing the Pearson correlation coefficient measures the linear relationship between pairs of variables from the respondent's data. This method revealed a strong correlation between fatigue occurring after working for 2-3 hours and a perceived increase in heart rate. This correlation is supported by a Pearson correlation value of 0.522 with a significance value of 0.002 (Table 6). It means there is a significant relationship between fatique and increasing heart rate. Another correlation data testing indicates a strong correlation between an increased heart rate during fatigue and increased sweat intensity for the respondents. This correlation is supported by a Pearson correlation value of 0.386 with a significance value of 0.035 (Table 7). Based on the results obtained through questionnaire analysis, particularly related to heart rate and fatigue, a measurement device will be developed to detect heart rate (HR), which will be converted into HRV through R-R signal measurements and sweating conditions during fatigue. It aims to improve the accuracy of fatigue measurements between 2-3 hours of online motorcycle drivers' working hours (Table 8).

Most of the 5 respondents who were measured for 2-3 hours showed symptoms of an increase in the R-R signal while working, reaching its peak after 2-3 hours of continuous work [31]. The R-R signal will then drop again when the driver rests. The four zones of respondents' working conditions will be detected, namely the initial condition (Zone 1), working condition (Zone 2), fatigue condition (Zone 3), and resting condition (Zone 4). The results of this measurement can be seen in Fig. 7 and Table 9.

Table 6. Pearson correlation between fatigue occurring after working for 2-3 hours and a perceived increase in heart rate

		If_you_feel_tired_does_your_pulse_feel_faster
If_you_feel_ fatigue_after working_for_2-3hours	Pearson Correlation	0.522
	Sig (2-tailed)	0.002
	N	30

Table 7. Pearson correlation between heart rate during fatigue and sweat intensity

		If_you_feel_tired_does_your_pulse_feel_faster
If_you_feel_tired_does_your_body_feel_sweaty	Pearson Correlation	0.386
	Sig (2-tailed)	0.035
	N	30

Table 8. Calibration result

Time	R-R Measurement Respondent 1 (ms)		Error	R-R Measurement Respondent 2 (ms)		Error	R-R Measurement Respondent 3 (ms)		Error	R-R Measurement Respondent 4 (ms)		Error	R-R Measurement Respondent 5 (ms)		Error
(Minutes)	Polar H10	Device	(%)	Polar H10	Device	(%)	Polar H10	Device	(%)	Polar H10	Device		Polar H10	Device	(%)
0	660	650	1.515	550	560	1.818	525	505	3.810	531	506	4.708	503	518	2.982
30	600	571	4.833	634	620	2.208	534	548	2.622	542	525	3.137	482	498	3.320
60	520	550	5.769	720	710	1.389	520	530	1.923	632	659	4.272	643	655	1.866
90	660	630	4.545	752	740	1.596	526	531	0.951	613	627	2.284	737	768	4.206
120	420	440	4.762	530	540	1.887	534	510	4.494	523	552	5.545	628	601	4.299
150	530	540	1.887	455	442	2.857	542	541	0.185	527	547	3.795	621	631	1.610
180	480	490	2.083	513	532	3.704	623	644	3.371	608	602	0.987	594	571	3.872
Average error			3.628			2.208			2.479			3.532			3.165
Total error									3.002620566						

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Table 9. Measurement of R-R conditions in 4 zones

Labels	Initial	Working	Fatigue	Take Rest
Min	620	720	853	753
Q1	776	844	884	790.5
Median	791	856	887	800.5
Q3	806	875.5	890.75	807.75
Max	858	935	902	878
IQR	30	31.5	6.75	17.25
Upper Outliers	1	1	1	1
Lower Outliers	1	1	1	1

Table 10. Measurement values from sensors obtained from Zones 1-4

RMSSD (ms)			
Zone 1	**Zone 2**	**Zone 3**	**Zone 4**
116.5547	72.24957	28.75761	80.47981
HR (bpm)			
Zone 1	**Zone 2**	**Zone 3**	**Zone 4**
90-100	110-120	130-145	100-110
Sweat Level			
Zone 1	**Zone 2**	**Zone 3**	**Zone 4**
Low	Medium	High	Medium

Description: Zone 1: Initial/Good condition (start of work), Zone 2 is declining condition, Zone 3 is tired condition, and Zone 4 is resting condition

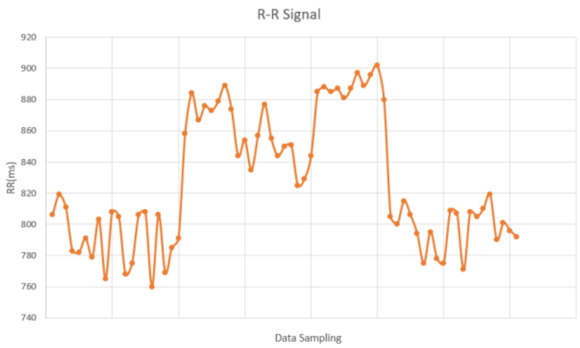

Fig. 7. Sampling plot graph (1 respondent) R-R signal data

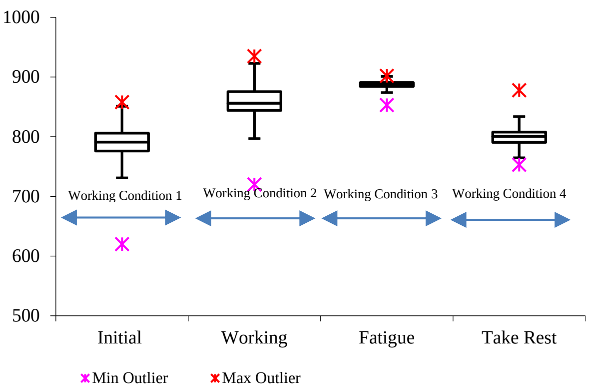

Fig. 8. Box whiskers plot graph from R-R to four working conditions

From the sensor measurement results depicted in the Box Whisker plot graph (Fig. 8) to measure the sensor measurement range [32], [33], it can be seen that the initial condition measurements have high variability and experience a significant decrease in variability when fatigued (the fatigue being analyzed is at the muscular level), then increase again during rest. Comparatively, the measurement ranges in these four conditions are not too different. It is also validated through HRV calculations obtained using the RMSSD method (Table 10), which shows that the rider's HRV in the initial condition is 116.5547 ms and continues to decrease during work to low conditions (72.24957 ms and 28.75761 ms) and then increases again during rest (80.47981 ms). The measurement results in Table 10 also show symptoms of an increase in HR and Sweat Levels in Zones 2 and 3 before decreasing in Zone 4. It shows an increase in HR and Sweat Levels during fatigue conditions after working about 2-3 hours, as in previous research findings from Kazmi [31]. The HR start to increase from the initial condition (Zone 1) when the driver starts working (Zone 2) and will reach its peak after 2-3 hours of work (Zone 3). it shows that the driver has experienced fatigue at work. The HR will decrease again when the driver rests after work (zone 4). Zone 2 and 4 results very close to each other because Zone 4 is a condition after resting, so RMSSD, HR, and Sweat Level approached Zone 2 (early work) levels

4. CONCLUSION

Based on our result from the questionnaire data processing, it can be concluded that every rider experiences fatigue after working for 2-3 hours in road conditions like those in Jakarta and its surrounding areas. When fatigued, they feel an increase in heart rate (Heart Rate) and sweating. HR identification is processed into R-R values, and HRV values, which are more accurate, are obtained. This measurement tool is used for identifying fatigue in different respondents. From the calibration results with the trusted measurement tool, this instrument shows good accuracy with an average error of about 3%. Using this measurement tool and the Box Whisker analysis method, it is also possible to determine the working conditions of respondents as a data group that has four working conditions those will be grouped into 4 zones as Zone 1 (Initial working condition or fit condition), Zone 2 (Declining condition), Zone 3 (Fatigue condition), and Zone 4 (Resting condition). This research is expected to accurately identify fatigue zones and reduce accident rates by identifying tired drivers who should not force themselves to continue driving their two-wheeled motor vehicles and should rest until they recover. The limitation of this study is that it was conducted during the daytime; however, it can be extended to activities during the nighttime. For the next development, using alternative personalization strategies, time-dependent modelling, and other types of information could potentially contribute to more accurate detection in the future.

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