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Mental Workload Assessment: The Relationship Between Physiological Heart Rate Variability and Subjective NASA-TLX Measures

[1]Auditya Purwandini Sutarto*, [1]Nailul Izzah, [1]Rahma Indah Kusumawardani
Corresponding Author: *auditya@uqgresik.ac.id
[1] Universitas Qomaruddin, Gresik, Indonesia

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ABSTRACT

The rapid advancement of technology has shifted many jobs to be dominated by mental or cognitive activities. Consequently, it is essential to measure mental workload (MWL) to ensure it does not exceed workers' capacity, which could increase error rates, pose safety risks, reduce productivity, and worsen well-being. This study aims to investigate the relationship between objective and subjective measures of mental workload. Using an experimental approach, HRV physiological signals were recorded from 30 subjects under four different conditions: baseline, MWL test 1 ("d2 attention" test), MWL test 2 ("switcher featuring" test), and recovery. Subjects were also asked to complete the NASA-TLX questionnaire to assess their perceived mental workload levels during the "d2 attention" and "switcher featuring" tests. The results of the repeated measures ANOVA showed significant differences in six HRV parameters across the four conditions. However, post-hoc tests revealed that only heart rate was able to distinguish between the two MWL tests. While NASA-TLX was sensitive enough to differentiate mental workload levels between the two types of tests, no significant correlations were found between each HRV index and NASA-TLX. This suggests a discrepancy between the two types of measures. Further studies are needed to employ different types of tests as well as other physiological measures.

Keywords
Cognitive
Correlation
Heart Rate
Mental Workload
NASA-TLX

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Introduction

Human work activities can be categorized into two components: physical and mental activities. Physical activity involves tasks predominantly involving bodily muscles, whereas mental or cognitive activity consists of work tasks primarily involving thought processes with minimal physical exertion. Both activities result in respective workloads: physical workload and mental workload [1].

The rapid development of technology and information has shifted the nature of work from being predominantly physical to focusing on mental aspects [2]. This shift underscores the importance of understanding mental workload levels so that organizations can design workload levels that are appropriate or exceed the capacity limits of workers. Excessive mental workload can lead to cognitive overload, increasing the risk of errors and accidents at work, reducing well-being, and ultimately diminishing work performance and organizational effectiveness [3].

Various studies have been conducted to measure mental workload both subjectively (self-reporting) and objectively. For example, a study by Zuraida and Aprillia [4] reported that 12 business government employees indicated high levels of mental, temporal, performance, and frustration aspects, but moderate physical aspects. Similarly, 18 machine operators reported high mental workload levels at PT PJL [5] and 17 production operators at PT Ujong Neubok [6]. All these studies utilized the National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire, a subjective measurement tool used to assess workload levels based on six dimensions: mental demands, physical demands, temporal demands, performance, effort, and frustration.

The subjective method of measuring mental workload has several limitations, including inaccuracy, inconsistency, dependency on the type of work, and the potential to disrupt daily work activities. Therefore, other objective measurement methods are needed. Various review studies have shown that measuring physiological body signals can provide more accurate information about an individual's mental workload [7], [8]. One of the popular physiological indicators used is heart rate variability (HRV), which is derived from electrocardiographic (ECG) signals.

HRV or RR interval refers to the time elapsed between two consecutive R waves (waves with the largest amplitude) or heartbeats [9]. HRV is influenced by the autonomic nervous system, which consists of two branches: sympathetic and parasympathetic nerves. The sympathetic nerves function as the "fight or flight" response during stress, leading to increased heart rate, blood pressure, and rapid breathing. Conversely, parasympathetic nerves promote relaxation, recovery, and energy conservation.

Research indicates that HRV reflects an individual's ability to regulate cognitive activity, emotions, and behavior to respond adaptively to environmental changes [10]. High HRV levels are associated with better cognitive function and stress adaptability [11], [12]. Conversely, low HRV indicates potential physical health issues, such as cardiovascular disease [13] and mental health problems [14].

Tao [8] reported that the majority of studies (67%) found heart rate to be sufficiently sensitive for detecting various levels of mental workload, while HRV features such as the root mean square of successive differences (RMSSD) and the ratio of low frequency to high frequency (LF/HF ratio) were deemed sensitive by 75% of the reviewed studies. Similarly, Charles and Nixon [7] found that 59% of the studies used cardiac activity as an indicator of mental workload, although not all features studied were proven to be sensitive in detecting different levels of workload.

Field measurements of mental workload have been conducted in various domains such as aviation [15], nuclear power plants [16], traffic control [17], remotely operated vehicle operations [18], and space flight [19]. However, such field studies have rarely been conducted in Indonesia. One example is Yasmin et al. [20], who found a relatively high-stress level in four store employees based on oxygen consumption and HRV parameters. Additionally, Wahyuning et al. [21] found that the heart rate levels and standard deviation of normal to normal (SDNN) HRV in train engineers were within normal ranges, although the locomotive cabin work environment influenced their stress levels and mental workload.

Despite the ecological validity advantages of field studies, the findings may not be accurate because of the numerous confounding factors that are difficult to control. Experimental studies offer a controlled environment that enhances the reliability and validity of HRV and mental workload measurements by minimizing external influences [22]This control facilitated precise data collection, variable isolation, and stronger causal inferences. Additionally, experimental studies allow for systematic testing of various conditions and interventions, providing a comprehensive understanding of the factors influencing HRV and mental workload.

Therefore, this study aimed to assess the extent of the mental workload using both subjective and objective indicators. Employing an experimental design, subjects performed two types of mental workload tests while their HRV was recorded. Specifically, we address the following research question:

1. Is there a significant difference in HRV during different types of mental workloads? (RQ1)
2. Is there a correlation between the subjective and objective measures of mental workload? (RQ2)

Material and Methods

A. Participant and Study Design

This study employed an experimental design to evaluate mental workload through both objective and subjective measures. The sample size was calculated using G-power 3.1 software [23]. For a paired-sample *t*-test with a significance level of alpha 0.05, a medium effect size of 0.25, and a test power of 85%, a minimum of 27 participants was required. To minimize the risk of dropout and missing data, we recruited 30 students from Universitas Qomaruddin, Gresik, Indonesia (mean age = 21.9 years, SD = 1.38 years). The sample included a relatively balanced gender distribution, with 55.9% male participants. Additionally, 26.5% of the participants were active smokers and all were right-handed. The eligibility criteria were as follows: 1) no neurological, heart, or psychiatric disorders; 2) not undergoing chronic medical treatment; and 3) no known allergies to adhesive substances or rubbing alcohol.

Participation was voluntary and written informed consent was obtained from all participants before the experiment began. The study protocol followed the ethical principles of the Declaration of Helsinki and was approved by the Local Research Ethics Committee.

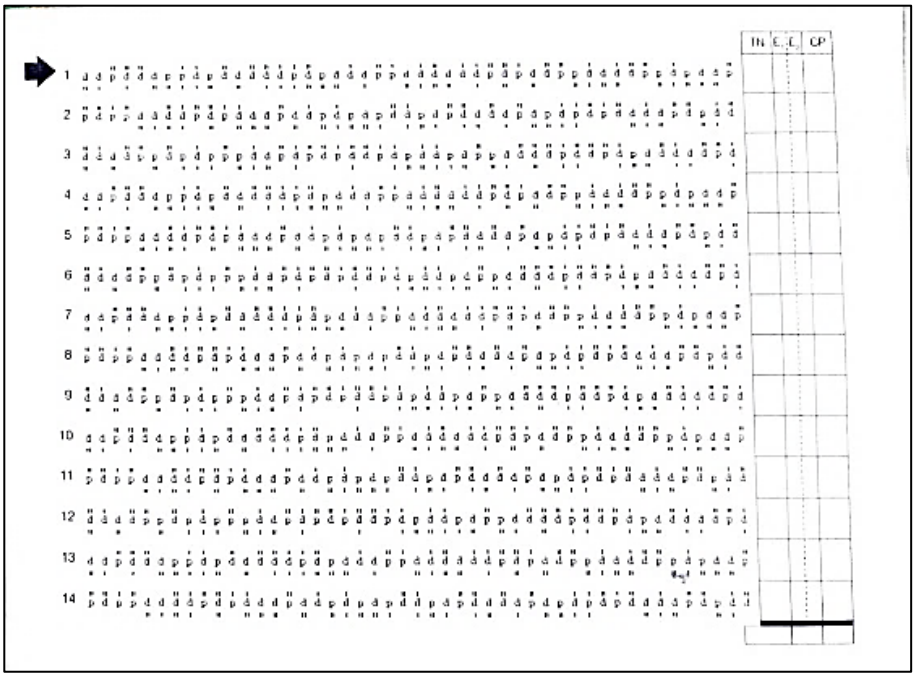
B. Instruments

1. d2 Attention Test

In this study, the original d2 Attention Test was administered in paper-and-pencil format. This neuropsychological test evaluates selective and sustained attention and essential cognitive functions in everyday life [24], [25]. Participants were required to identify and cancel out target stimuli, defined as the letter "d" with two apostrophe marks, which may be positioned above or below the letter, among a variety of distractors. The test consisted of 14 rows, each containing 47 letters. Participants had 20 seconds to cancel as many target symbols as possible in each row before moving on to the next row. The total duration of the test is approximately five minutes.

2. Switcher Featuring Test

The Switcher Featuring Test is a computerized cognitive assessment included in the Psychology Experiment Building Language (PEBL) test battery [26]. This task measures cognitive flexibility and divides attention by requiring participants to repeatedly switch between different rule dimensions. As shown in Figure 2, during the task, participants viewed a screen displaying ten distinct colored shapes, each sharing only one common dimension with another object (color, shape, or letter).



Source: Brickenkamp [24]

Fig. 1. d2 attention test in paper-pencil version

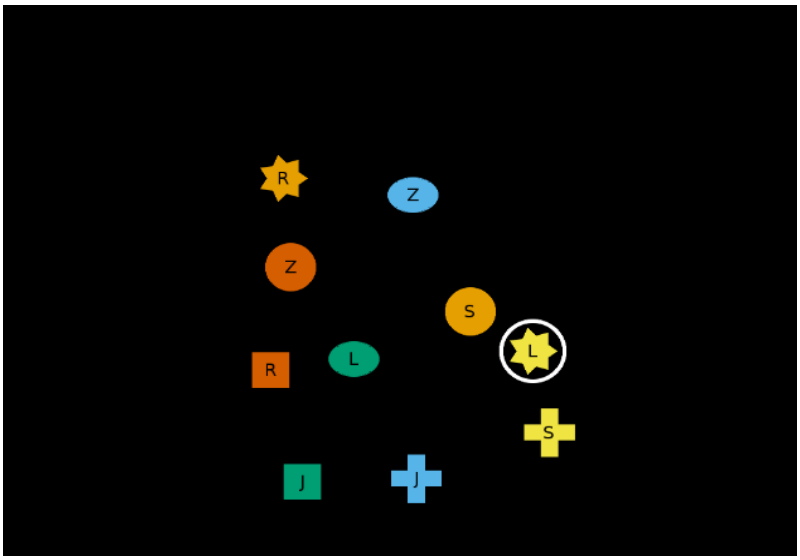
Participants were prompted to select a matching object based on a displayed shape, color, or letter after one object was circled. Following a successful match, they must switch to a different feature to match the object based on that new feature and then switch back to the previous feature. The task was divided into three sessions, each consisting of nine blocks with ten responses per block. The task structure included the following:

- Condition Alternate Switch: In the first three blocks, participants switch between two of the three feature rules, with each block using a different pair combination.
- Condition Fixed Switch: In the next three blocks, participants switch between the three feature rules in a consistent order, with the order changing in each block.
- Condition Random Switch: In the final three blocks, participants switch between the three feature rules randomly, making the next rule unpredictable.

The participants completed a brief practice round before the main task to familiarize themselves with the procedure. The main task lasts approximately five minutes.

3. NASA-TLX

The NASA Task Load Index (NASA-TLX), developed by NASA's Ames Research Center, is a widely recognized tool for measuring perceived workload across various domains [27]The NASA-TLX comprises six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration. In this study, it was administered using paper and pencil.



Source: Mueller and Piper [26]

Fig. 2. Switcher Featuring Task in PEBL Battery Software

Participants were instructed to rate their perceived workload for two distinct tasks—the d2 attention test and the switcher-featuring task —using a 100-point scale. This method provides a comprehensive assessment of the various dimensions of the workload.

4. Polar H10

The inter-beat intervals (IBI) and RR intervals of HRV were recorded using a Polar H10 chest-strap device (Polar Electro, Kempele, Finland), which has been validated against a three-lead ECG Holter monitor [28] . The elite HRV app is used to log the IBIs on a smartphone. The raw data were exported as a text file for subsequent import into Kubios HRV software [29]. Artifact filtering in the IBI time series was performed at a medium correction level during preprocessing. The software then conducted both time-domain and frequency-domain analyses of the IBI.

In this study, we selected several HRV metrics based on the recommendations of [30], consisting of both the time and frequency domains. For time-domain metrics, we included the mean heart rate (Mean HR), standard deviation of R-to-R intervals (SDRR), root mean square

of successive differences (RMSSD), and percentage of successive normal sinus RR intervals exceeding 50 ms (pNN50). The frequency-domain metrics included low frequency (LF), high frequency (HF), and the ratio of low to high frequencies (LF/HF ratio). Both LF and HF are expressed in normalized units (nu), representing the proportion of power within a specific frequency band relative to the total power of the combined LF and HF bands.

C. Procedure

After obtaining consent, the Polar H10 device was securely fastened to the participant's chest, just below the pectoral muscles. Participants were instructed to avoid caffeine, smoking, and heavy meals for two hours before data collection, in line with the established HRV research methodology [30]. This study prioritized the control of transient variables that could affect HRV. Measurements were taken while the participants sat in front of a 14" laptop screen. Baseline and recovery data were collected as the participants remained still for five minutes. The mental workload tasks, d2 attention test, and feature-switching tasks were performed sequentially. A manual timestamp was used to differentiate the recordings between two consecutive sessions. This enabled alignment with HRV data analyzed later using the Kubios HRV software [29] and minimize the risk of interruptions between sessions.

D. Data Analysis

Descriptive statistics were used to report the mean and standard deviation of all HRV indices and the total NASA-TLX scores. To address RQ1, repeated measures ANOVA (RM ANOVA) was employed to assess the differences in each HRV index across the four conditions. If significant differences were found, post-hoc tests with Bonferroni correction were performed. Moreover, to examine the differences in perceived mental workload, indicated by NASA-TLX scores, between the d2 attention test and the switcher featuring test, we conducted a paired t-test. To address RQ2, Pearson's correlation analysis was used. All analyses were conducted using the Statistical Package for the Social Sciences (SPSS) version 25.0.

Results and Discussion

Table 1 displays the descriptive statistics, including mean and standard deviation, of HRV indices across the four conditions: baseline, MWL1 (d2 attention test), MWL2 (switcher featuring test), and recovery. Table 2 summarizes the results of the repeated measures ANOVA (RM ANOVA) and paired t-tests, indicating significant differences in the five HRV indices (heart rate, SDNN, RMSSD, LF, and LF/HF ratio), as evidenced by their respective F values across the four conditions. No significant differences were observed in the high-frequency (HF) component of HRV. Further posthoc tests revealed that these differences were primarily

observed between the baseline and other conditions, consistent with previous studies that differentiated between relaxed or non-stress conditions and mental workload engagement [31], [32]. However, we could not demonstrate the sensitivity of HRV in distinguishing between different mental workload tests, a finding that aligns with prior studies that also showed inconsistency in this area [8].

Table 1. Descriptive Statistics of HRV and NASA-TLX

Index	Baseline		d2 attention (MWL1)		Switcher (MWL 2)		Recovery	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
HR	82.73	9.4	89.2	13.25	86.06	10.68	83.5	9.25
SDNN	40.68	14.29	31.87	14.29	34.18	12.79	40.26	16.51
RMSSD	40.59	24.82	33.41	20.61	33.06	16.43	35.54	20.47
LF	53.97	20.20	53.83	17.73	58.85	14.75	63.73	16.83
HF	45.89	20.19	45.92	17.67	51.07	55.21	36.2	16.82
LF/HF	1.74	1.49	1.57	1.19	1.74	1.009	2.98	3.10
NASA TLX		---	67.5	15.50	56.2	16.15		---

* SD = standard deviation, HR: heart rate, SDNN: Standard deviation normal to normal, RMSDD: Root mean square standard deviation, LF: low frequency, HF: High frequency

Table 2. ANOVA or t-test

Index	*F* or *t*-test*	*p*-value	Post-hoc**
HR	12.637	<.001	Baseline vs Recovery Baseline vs Test 1 MWL 1 vs MWL 2 MWL 2 vs Recovery
SDNN	10.578	<.001	Baseline vs MWL 1, Baseline vs MWL 2 MWL 2 vs recovery
RMSSD	3.964	.022	Baseline vs MWL 1
LF	7.243	.001	Baseline vs recovery MWL 2 vs recovery
HF	1.298	.269	
LFHF	7.032	.005	Baseline vs recovery
NASA TLX	4.884	<.001	

* t-test for comparing NASA-TLX scores. **Post hoc test was performed when ANOVA was found significant

For example, an earlier study [33] found that the heart period, but not HRV, was the only sensitive indicator for distinguishing mental effort investment as a function of task difficulty in the tunnel task of a flight simulator. Other studies have shown that HRV cannot detect manipulation of workload and levels within the same tasks [34], [35]. In contrast, this finding does not corroborate previous studies [36], [37], [38], which demonstrated the sensitivity of some HRV parameters to changes in various manipulations of mental workload. This inconsistency may be explained by the possibility that the tasks used in this study did not evoke different levels of mental workload [39]. It appears that both the d2 attention and switcher featuring tests occupied relatively similar cardiovascular activation, resulting in similar HRV responses. Nickel and Nachreiner [40] also proposed that HRV is an indicator of

arousal or emotional strain, rather than mental workload. Nevertheless, this lack of evidence warrants further investigation with more pronounced levels of mental demands with longer durations, such as mathematics-based or sustained visual-monitoring tasks.

Regarding subjective mental workload assessment, a significant difference was observed between the d2 and switcher-featuring tests. The subjects reported a higher workload when performing the d2 attention test, even over a relatively short duration. This may be attributed to their lower familiarity with the paper-pencil format of the d2 attention test compared with the computer-based switcher-featuring test. The sensitivity of NASA-TLX in this study aligns with previous findings [31], [37]. Therefore, studies aimed at detecting mental workload based on HRV features using machine learning approaches often utilize NASA-TLX as the ground truth to label mental workload states [41], [42].

As shown in Table 3, contrary to expectations, no significant correlation was found between any HRV indices and NASA-TLX scores during the d2 attention test and switcher-featuring test. Pearson Correlation Coefficient between HRV indexes and NASA-TLX Scores during d2 attention test and Switcher featuring test

	d2 attention (MWL1)	Switcher (MWL 2)
Heart rate	0.195	-0.257
SDNN	-0.111	0.305
RMSSD	-0.202	0.199
LF	0.164	-0.282
HF	-0.150	0.052
LFHF	0.152	-0.290

This finding suggests that regardless of the participants' perceived mental effort, their psychophysiological responses may remain consistent. In addition, previous research [43] emphasized that subjective measures are the most sensitive to changes in mental workload, followed by performance and psychophysiological measures.

Conclusion

In conclusion, we found that physiological signals derived from HRV measures can distinguish between baseline states and engagement in a mental task. However, the sensitivity of HRV indices in detecting different mental workload tasks was less convincing than subjective assessments using the NASA-TLX. This discrepancy may be attributed to the nature of the tasks, their short duration, and the individual variability in physiological responses. The lack of correlation between HRV and NASA-TLX measurements suggests that mental workload is a multifaceted construct that may not be fully captured by HRV alone.

Limitation and Suggestions

This study has several limitations. One significant limitation is the small sample size and the homogenous characteristics of the sample (university students). Future research with larger and more heterogeneous samples would enhance the generalizability of these findings. Second, given the observed lack of sensitivity of HRV in detecting different levels of mental workload, future studies should incorporate other physiological indicators such as electrodermal activity or galvanic skin response. Additionally, employing mental workload stimulus tests with clearly defined levels of demand would improve the assessment of mental workload.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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Authors



Auditya Purwandini Sutarto is a Lecturer in the Department of Industrial Engineering at Universitas Qomaruddin Gresik, Indonesia. She holds a bachelor's degree in Industrial Engineering from Institut Teknologi Bandung, a Master's degree in Mathematics from Universitas Gadjah Mada, and a Doctorate from the University of Malaysia Pahang, Malaysia. With over 20 years of experience as a lecturer, she teaches subjects including ergonomics and work design systems, statistics, and research methodology. Her areas of expertise include cognitive ergonomics and psychophysiology. (email: auditya@uqgresik.ac.id).



Nailul Izzah holds a Master's degree in Biostatistics from Universitas Airlangga, Surabaya, Indonesia. She is currently a lecturer at the Department of Industrial Engineering at the Universitas Qomaruddin, Gresik, Indonesia. She has extensive experience in teaching mathematics and statistics at the university level. Her research interests include applied mathematics and industrial statistics. (email: nailulizzah@uqgresik.ac.id).



Rahma Indah Kusumawardani holds a Bachelor's degree in Engineering from Universitas Qomaruddin, Gresik, Indonesia. She has served as a research assistant at the Laboratory for Ergonomics at Universitas Qomaruddin for the last three years. Her responsibilities include conducting laboratory work and assisting with research in the field of ergonomics. (email: rahmaindahk20@gmail.com).